A REGRESSION MODEL FOR PREDICTING ACADEMIC SUCCESS OF PROSPECTIVE STUDENTS IN THE AFIT GRADUATE LOGISTICS MANAGEMENT PROGRAM

THESIS

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THESIS

Presented to the Faculty of
the School of Systems and Logistics
of the Air Force Institute of Technology
Air University
In Partial Fulfillment of the
Requirements for the Degree of
Master of Science in Systems Management

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December 1989

Approved for public release; distribution unlimited

## Acknowledgements

A project of this size could not have been completed without the help of good friends and dedicated professionals. I would like to sincerely thank my thesis advisor, Maj Kenneth Bauer, for his contageous enthusiasm and especially for his patience with me. Thanks also to Dr. Guy Shane and Professor Dan Reynolds for their help with motivation and with computer problems.

Consent to review graduates' records was granted by Colonel Dorothy L. Stewart, Director of AFIT Admissions. Thanks especially to Captain Steven Gurnell and his friendly staff in the Records/Registration Division, who were very helpful during long hours of data collection.

Very special thanks is extended to an old friend, Captain Skip Langbehn. In the midst of his own AFIT academic pressures, he offered his considerable expertise and personal computer resources to help solve serious computer difficulties. For the kind of self-sacrificing friendship seldom seen these days, Skip, thank you.

And finally to my very best friend, my wife Lynda, I offer thanks for patience, for understanding, for encouragement, for sage advice, and for bringing me breakfasts at the word processor.

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## Abstract

Counselors in the Admissions Division at the Air Force Institute of Technology currently determine academic eligibility of graduate programs candidates subjectively on the basis of criteria defining minimum acceptable undergraduate grade point averages (UGPA) and graduate admissions test scores. The determination could be made more uniformly and efficiently by a regression model that could predict each candidate's final graduate grade point average (GGPA) given his or her UGPA, test scores, and other background information. This study developed and validated such a model using data collected on 140 students of the Graduate Logistics Management (GLM) classes of 1986 through 1989. (EG)

The predictor variable found to be most highly correlated with GGPA was need for achievement. Stepwise regression was used to select from among 31 predictors, including admissions test scores, UGPA, age, rank, math GPA, and time since undergraduate degree. Two models were thus developed--one for students with GRE scores and one for students with GMAT scores.

The models gave $R^2$ values of .59 and .54. This relative success was attributed to three factors: 1) considerable variety of input factors among GLM students; 2) the selection

of a single, uniform curriculum for study; and 3) a highly correlated predictor formed as the product of UGPA and a rating of the admissions competitiveness of the undergraduate institution. This predictor acted as the UGPA adjusted for the difficulty in achieving that avarage.

Regression assumptions were checked through residual analysis. A graphical demographic report is included.

# A REGRESSION MODEL FOR PREDICTING ACADEMIC SUCCESS OF PROSPECTIVE STUDENTS IN THE AFIT GRADUATE LOGISTICS MANAGEMENT PROGRAM

## I. Introduction

The Air Force has an important need for officers who can effectively manage the diversity and complexity of Air Force logistics systems and related programs. To fill this need, the School of Systems and Logistics of the Air Force Institute of Technology (AFIT) offers a resident master's degree program in Logistics Management. Enrolled officers major in one of five management options: Maintenance, Inventory, Transportation, Acquisition Logistics, or Logistics. The last of these options, Graduate Logistics Management (GLM), is the most general, providing students with a systems perspective of the total logistics environment (6:167-174).

### General Problem

The problem of identifying the most qualified candidates for the GLM curriculum and all other AFIT resident master's degree programs is shared by AFIT, HQ USAF, and AFMPC. These organizations determine academic eligibility, assess military availability, and make final selection, respectively.

The Admissions Division of the AFIT Directorate of Admissions/Registrar reviews academic records of student candidates to determine academic eligibility. Admissions obtains academic records from two sources. First, AFIT maintains an Officer Education Transcript Repository in order to document the academic achievement of all Air Force officers. Admissions may review this repository and "centrally identify" officers who meet the basic academic eligibility criteria. Second, motivated persons may apply by submitting requests for academic evaluation, including transcripts and standardized test scores. Those applicants that meet the eligibility criteria are awarded "Letters of Eligibility," while ineligible applicants receive "Letters of Guidance" suggesting ways of meeting eligibility requirements (6:9-10).

HQ USAF assesses the military availability of all centrally identified officers and applicants who are academically eligible (6:13). An Air Force officer can not be considered available for an AFIT tour unless he or she: 1) is medically unrestricted for worldwide duty; 2) is serving in the grade of colonel or below; 3) has a competitive military record; 4) is available for reassignment; and 5) has at least three years of intervening service since his or her last PCS education assignment (9:4-11,4-12).

AFMPC convenes a continuous selection board beginning in July to consider all eligible and available officers for AFIT

entry during the next fiscal year. Factors considered by the board include:

> promotability, career progression, prior academic and assignment experience and the qualificantions of the individual to perform in positions requiring the education to be obtained through AFIT. (9:4-17)

Applicants, frequently referred to as "volunteers," are given higher priority throughout the selection process than centrally identified officers (17).

Graduate students in logistics management are big investments in the future of the Air Force. The average cost of educating a single GLM student in FY 1987 was $109,298 (8). In order to get an adequate return on this investment, AFIT must insure that its students graduate and apply their new skills to real Air Force logistics problems. Failure to graduate hurts not only the Air Force but also the unsuccessful student, whose career could be jeopardized by an unsatisfactory training report. Academic survival is the responsibility of the enrolled student. However, the AFIT selection process should offer enrollment only to applicants with a high probability of academic survival.

Specific Problem

As mentioned above, the eligibility determination made by AFIT is an important part of the general selection problem. Eligibility criteria are currently used subjectively, but the Admissions Division could make more efficient use of an objective method for determining eligibility.

The Admissions Division currently requires candidates for the GLM option to meet certain minimum criteria. Although a Bachelor's degree in practically any major is acceptable, candidates must have completed college algebra with a grade of C or better (9:4-48). An undergraduate grade point average (UGPA) of 2.5 on a 4.0 scale is required as well as a Graduate Record Examination (GRE) General Test score of at least 1000 or a Graduate Management Admission Test (GMAT) score of 500 or better (6:10).

In practice, the above criteria are flexibly applied to candidate records. For example, an Admissions Division counselor might allow an applicant's 3.95 UGPA to compensate for a sub-1000 GRE score. The extent to which such compensation may be applied is not clearly defined, however, allowing subjectivity to enter into the eligibility determination. Admissions will frequently send a borderline academic record to an Academic Standards Committee of Logistics Management faculty members for recommendation (17). This committee will assess the undergraduate curriculum and its potential support of the GLM curriculum, adding more subjectivity to the eligibility determination.

The current process of subjectively determining academic eligibility consumes considerable time and energy of highly trained admissions counselors and faculty members. Time and manpower requirements could be significantly cut by incorporating an objective, statistical model that could predict the degree of academic success of prospective GLM

students based on information about their background. Inputs would include UGPA and scores on the GRE and GMAT, of course, but could also include any other quantifiable information available to the Admissions Division. The degree of academic success output by the model could simply be a dichotomous indication: "will graduate" or "will not graduate" from AFIT. A more informative output that would allow the Admissions Division to fine-tune the eligibility determination would be predicted graduate grade point average (GGPA). Mr. Richard H. Lee, Chief of the Admissions Division, believes the current process could be improved by the use of such an objective model (17).

The overall purpose of this thesis is to build a statistical model that can be used to predict the academic success of prospective GLM students.

## Research Objectives

This study has two research objectives. The first research objective is to develop a statistical model that inputs information about past GLM graduates and outputs estimated GGPA's that are close to actual GGPA's earned. Input information will include UGPA, scores on the GRE and GMAT, undergraduate mathematics grades, and many other predictor variables. The second research objective is to validate the proposed model so that the Admissions Division can use it to predict the GGPA's of prospective GLM students.

## Investigative Questions

To help reach the research objectives, the following investigative questions will be addressed:

1. How well does UGPA correlate with GGPA?

2. What roles do GRE and GMAT scores play in predicting GGPA?

3. How is GGPA affected by military factors such as rank, commission type, aeronautical rating, and time in service?

4. Does personal information such as gender and age help predict GGPA?

5. Is GGPA influenced by the strength of the undergraduate math and statistics background?

6. How can motivation be quantified and used as a predictor of academic success?

## Overview

This chapter defined the general Air Force problem of selecting the most qualified candidates for the AFIT graduate program in Logistics Management. Also defined was the AFIT Admissions Division's specific problem of efficiently determining the academic eligibility of GLM candidates. The intent of this study, to develop an objective statistical model as an aid to the eligibility determination, was mapped out through research objectives and investigative questions. The next chapter will review the related literature and provide an overview of the statistical method to be used.

Chapter 3 will detail how the research objectives will be achieved, and Chapter 4 will analyze the results of the research. The last chapter will discuss policy implications for management and recommendations for further research.

# II. Background

This chapter will review related literature and give a brief overview of the statistical technique chosen for this investigation. This type of research is extremely popular within the academic community, partially because no universal predictive model can be developed that will apply to all academic institutions, curricula, and applicant populations. Consequently, local prediction studies that apply specifically to particular academic situations are the best approach to selecting the most qualified applicants (31:61). Only those literature topics directly related to the current study will be covered here.

## Criteria of Academic Success

Several criteria have been used as measures of academic success in graduate school, including achievement examination scores, faculty ratings other than by grades, self ratings, and GGPA. Of these, GGPA is the most common and probably the easiest to use (25:1-2). Another common criterion is the so-called "did graduate/did not graduate" dichotomous variable distinguishing students who complete all degree requirements on schedule from students who do not.

In his 1977 AFIT predictive study, Keith developed models for both GGPA as criterion and "did graduate/did not

graduate" as criterion. In defending the latter variable as the "ultimate" criterion variable (16:6), he asked

> Can it be said that a degree candidate with excellent grades who does not graduate because he cannot satisfactorily complete his thesis work is a "success" based on GGPA, whereas the student with the lowest GGPA in his class who receives his degree is a "nonsuccess?"

Defending his choice of GGPA as the better criterion, Prokopyk (21:7) pointed out that the Keith study did not distinguish between students who complete degree requirements after their scheduled graduation date and students who never complete degrees. According to the AFIT Catalog (6:42), a student may take as many as five years to complete all degree requirements. Prokopyk concluded that a student "who graduates late should not be considered an unsuccessful student." I agree with Prokopyk, and thus GGPA will be the criterion variable in this study.

### Predictor Variables

Types of information about degree candidates that can be used to predict their academic success are known as predictor variables. Numerous predictors have been used in previous research, but only the more common or interesting are discussed here.

Perhaps the most universally used predictors of graduate school success are scores on the Graduate Record Exam (GRE) General Test. This standardized aptitude test is designed to assess academic knowledge and skills relevant to graduate

study (13:25). The GRE is divided into three sections that measure verbal, quantitative, and analytical abilities.

Predictors used extensively by graduate schools of business and management are scores on the Graduate Management Admission Test (GMAT). This is also a standardized test, but is more like an achievement test than the aptitude-measuring GRE. Aptitude tests measure knowledge gained over a long time period under relatively uncontrolled conditions. By contrast, achievement tests measure learning and skills acquired over a shorter time period and in a more structured setting (30:10-11). The GMAT is divided into verbal and quantitative sections.

The undergraduate grade point average (UGPA) is a widely used predictor that does not share the predictive success of GRE and GMAT scores (29:184; 25:1). The main reason for lower correlations with GGPA is that UGPA is not standardized, as are the GRE and GMAT. Grading variations between curricula, courses, and teachers give the UGPA an entirely different meaning for each graduate of the same undergraduate institution. If the GPA composite were made up of equivalent components, it would be a more reliable measure (12:13) and UGPA would have more validity as a predictor (21:12).

Although UGPA is an unreliable measure for students in the same college, it is more generally unreliable when comparing students from different colleges. Clearly, different institutions offer different degrees of educational

quality, and a UGPA of 3.5 earned at, say, the Massachusetts Institute of Technology does not reflect the same degree of educational accomplishment as a 3.5 from a number of small community colleges (25:13). If UGPA could be adjusted for the educational quality of the college attended, then perhaps UGPA reliability would increase, making it a more valid predictor of GGPA (21:12,14).

In his 1988 AFIT thesis, Prokopyk (21) sought a "quality of schools" indicator that would compensate for the low predictive validity of UGPA. He settled on a rating of admissions competitiveness, assuming that this factor is directly related to academic difficulty and therefore to the quality of undergraduate education. Prokopyk included this 6-level "quality of schools" rating as an indicator variable in his multiple regression on GGPA. It appears that, since the stepwise regression method employed considers each predictor variable independently, "quality of schools" was not interpretted as an adjustment to UGPA but rather as just another predictor alongside UGPA. Consequently, "quality of schools" did not enter his final models and did not compensate for low UGPA predictive validity. The current study will include the same admissions competitiveness rating (2:vii) as a seperate predictor but will also multiply it by UGPA to form another predictor. This latter step will force the stepwise regression procedure to consider both factors in the same composite variable. The composite variable might be

interpretted as the UGPA adjusted for the degree of difficulty in attaining that grade average.

It seems reasonable that the degrees of students' motivation to study should help explain variation in their GGPA. Although a great deal of work has been done in this area, results have been mixed, owing partly to the difficulty in measuring motivation. Using a surrogate motivation variable, Keith found that whether a student did or did not volunteer for AFIT was the best single discriminator between degree receipt or non-receipt (16:42). Yet, Senger and Elster's thorough 1974 literature review reported dissapointing predictive power for motivational measures (25:16).

Perhaps the most hopeful motivational measurement has been the need for achievement, or n Ach, which has been found to be correlated with school grades (1:255). Henry Murray first conceptualized n Ach as "behavior toward competition with a standard of excelence" (4:44). Steers and Braunstein (28) developed a very practical instrument for measuring the need for achievement called the Manifest Needs Questionnaire (MNQ). Five statements describe patterns of behavior thought to be typical of an individual attempting to satisfy the need for achievement in the work place. Subjects are asked to indicate on a seven-point scale the degree to which each statement describes their own actions at work. The n Ach score is assessed by averaging the five responses. A team of AFIT researchers (27:293) has determined the reliability of n

Ach to be modest, but they conclude that it does "approximate a level of internal consistency suitable for experimental instruments." In the current investigation, the MNQ will be used to measure n Ach, which will be checked for correlation with GGPA.

Many other predictors have been used in graduate school prediction studies. Predictors encountered by Senger and Elster include the number of courses taken in a particular discipline, grades in specific courses, candidates' written statements, biographical data such as age and marrital status, and personality and interest measures (25:2-3). Humphrey (14:97) found "time since last math course" and "math undergraduate GPA" to be important predictors of AFIT success for Graduate Engineering Management students. Similar variables that reflect math background will be included in the current investigation.

## Population Homogeneity

Van Scotter (30:70) confirmed earlier findings that correlations between predictors and GGPA vary significantly between master's degree programs within the same school. He also found that predictor/criterion correlations for a large sample combining students in several programs were smaller than those for subsamples of students in the same program. Keith also concluded that

> decreasing the homogeneity of the group, that is, combining students majoring in different fields of study, decreases the predictive power of the independent variables. Students in different disciplines should not

be combined for GGPA predictive purposes. (16:41)

A single curriculum group of AFIT students will be used in the current prediction study in hopes of building a highly successful model.

## Overview of Multiple Linear Regression

Several statistical methods have been employed in past graduate school success prediction attempts. Most models with "did graduate/did not graduate" as the criterion of success have used discrimant analysis or the Automatic Interaction Detection algorithm. Other methods have used bivariate and canonical correlation analyses. The most frequently used method and the one chosen for this study is multiple linear regression (MLR).

The correlation coefficient, r, measures the strength of the linear relationship between two random variables (20:319). Multiple correlation allows one to determine how much of the variation in a criterion variable is associated with a set of predictor variables (15:226). Toward this end, one seeks that particular weighted combination of the predictor variables that correlates most highly with the criterion variable. Given a random sample of data on the predictors and criterion, the method of least squares calculates the weights in the most highly correlated weighted combination of predictors. When more than one predictor variable is included and the weights are algebraically linear (20:475), the least squares method is referred to as multiple

linear regression (MLR). The equation, or model, developed in MLR is, generally

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (1)$$

where y is the criterion variable, x's are predictor variables, $\beta$'s are the weights or parameter estimates, and $\varepsilon$ is a random error term.

The coefficient of determination, $R^2$, for an MLR model is the proportion of the variability in the criterion variable that is accounted for by variation of the set of predictor variables (20:490-492). If predictor variables in the model are correlated with one another, $R^2$ is not simply the sum of the squared correlation coefficients of each of the predictors. In this case, the predictors "account for overlapping pieces of the variability" in the criterion variable.

Four basic assumptions must be satisfied in order to use MLR. These are explained by Ott (20:581) as follows:

1. The expected value of the random error terms for any given setting of the predictors is zero.
2. The variance of the random error terms is the same for all settings of the predictors.
3. For any given setting of the predictors, the random error terms are distributed normally.
4. All the random error terms are independent.

## Summary

This chapter briefly reviewed the extensive literature relating to prediction of academic success in graduate schools. Important predictor variables were discussed, including an admissions competitiveness rating and the need for achievement. The importance of population homogeneity was stressed, and an overview of multiple linear regression was provided. Lessons learned through literature research will be used to formulate the methodology for this investigation, as described in the next chapter.

## III. Methodology

This chapter datails the plan for accomplishing the research. The first of four sections describes data collection. Operational definitions of variables are given next. Model development and model validation methods are proposed in the last two sections.

### Data Collection

Most of the data will be obtained from the Records/Registration Division of the AFIT Directorate of Admissions/Registrar. This office maintains academic files for all students who have attended AFIT in residence. Data from each student's file will be transcribed by hand to a data collection sheet (Appendix A). I will not have access to updated files of the GLM 89S class (those GLM students scheduled to graduate in September 1989) until final grades are processed in mid October.

Data missing from individual files may be obtained through an ATLAS database search. AFMPC maintains this database of information on all active duty and reserve Air Force members. Furthermore, a survey will be administered to GLM 89S students in order to measure the need for achievement. All personal data will be handled according to the provisions of the Privacy Act of 1974.

Population Studied. A single curriculum group of students was selected for this investigation in an attempt to

obtain a highly successful model. Recall that increasing group homogeneity by focusing on narrower curriculum groups has increased the predictive power in previous research. It is instructive to think of this homogeneity as process uniformity in an educational system that inputs variously qualified students, educates and evaluates academic performance, and outputs logiticians with GGPA's. All GLM students input to this system are processed uniformly, taking basically the same sequence of courses.

The GLM option was selected to be the single curriculum group for study because of the considerable variety of background among its students. The Graduate Programs Director (18) believes GLM students exhibit a greater variety of undergraduate majors and Air Force experience than any other student group in the School of Systems and Logistics. If these students are inputs to a system that evaluates academic performance, then background characteristics of these students may be quantified as predictor variable inputs to an MLR model that predicts academic performance. Recall that MLR predictor inputs attempt to explain the variation in the criterion output. It is logical, then, that the greater the input variation of predictor values, the greater the potential for explanation of criterion variability. It is this input variation that is sought with the selection of the GLM option.

The population examined included all 140 students, excluding foreign service officers, who entered the GLM

option in June 1985 or later and received a master's degree in the same option prior to October 1989. (The motivation survey was administered only to the 1989 class.) Students entering in 1984 and earlier were excluded from the study due to a significant curriculum change instituted in 1985. The GLM curriculum expanded from 62 to 66 graduate quarter hours, and added required courses in Life Cycle Costs, Decision Support Systems, and Computer Programming (26:4-6). The population was restricted to students who have taken essentially the same courses in order to further achieve process uniformity as described above. The resulting sample size (n = 140) is smaller than those of previous AFIT prediction studies; however, it is hoped that attention to process uniformity will yield better results.

Data Manipulation. Raw data will be transferred from the data collection sheets and survey response forms to a personal computer spreadsheet program. The spreadsheet's database capabilities, namely, sorting and searching, will facilitate familiarization with the database as a whole. A natural by-product of this familiarization will be demographic information on the population studied. Although not required for the development of a prediction model, a demographic report on the GLM classes of 1986 through 1989 could be of considerable interest to the AFIT Department of Logistics Management.

The raw data spreadsheet will next be quantified by coding the variables as per Appendix B. This coded

spreadsheet will then be converted to ASCII format and uploaded via modem to the AFIT VMS-based VAX minicomputer. The data in this final form can then be input to the statistical analysis software to begin model development. Data is available on a 5.25 inch flexible disk upon request.

## Variable Definitions

This section defines variables that may be used in the statistical analysis. Most of these variables will be raw data elements from the data collection sheets. Others will be mathematically derived from raw data elements. Raw data elements such as name and social security number will only be used at an intermediate level for data identification and organization. Appendix B is a key to the database.

All information to be used in the statistical analysis must be quantified, that is, measured on a numerical scale. The four measurement scales to which each data element must be appropriately matched are the nominal, ordinal, interval, and ratio scales (10:87).

Numbers on a nominal scale act merely as labels and not as indicators of ranking or magnitude (15:19). In the present study, for example, the dichotomous variable SEX is nominally measured by assigning females the value 0 and males the value 1. A characteristic that can be placed in one of k mutually exclusive and collectively exhaustive categories should be represented in a regression study by k- 1 dichotomous "dummy" variables. Each dummy then defines the

presence, 1, or absence, 0, of the characteristic in that category. As many as kdummy variables would result in a multicollinearity problem, since the dummies are dependent on one another (15:268-269).

On the ordinal scale, numbers represent rank ordering of a characteristic; however, the distance between the ranks may vary, undefined by the scale. The interval scale allows rank ordering as well as definition of equal distance between ranks. The ratio scale is the most informative of all, providing rank ordering, equal distances between ranks, and the additional property that equal ratios of values are also equivalent (15:19).

Technically speaking, variables measured on an ordinal scale should not be included in a regression study. Yet determining whether a variable is ordinal or interval is a matter of individual judgement. Many researchers justify their use of questionably ordinal data in regression by assuming equal distances between ranks (10:89,91). I will make such an assumption for this investigation and will regress with several variables that are not clearly interval in nature. These variables will be referred to as "indicator" variables.

Many of the 32 variables described below are time-critical. That is, the status defined by a time-critical variable is likely to change during the subject's tour at AFIT. Therefore, variables such as age, rank, and service time reflect status at the time the subject enters AFIT.

Six variables are general in nature. SEX is a dichotomous indicator of gender. AGE is the difference in years between two raw data elements, AFIT class entry date and birthdate. Three dummy variables, namely AF, NAVY, and CIV, are established to identify the military branch or civilian component. All subjects studied are either Air Force officers, Navy officers, civilians, or Army officers. The latter are identified by a zero in each of these three dummy variables. Finally, RANK is an assumed ordinal variable indicating pay grade. There is no official correlation between military rank and civilian grade (7:5-42). For purposes of protocol, however, rank/grade equivalencies do unoffically exist. In accordance with this system, RANK equates O-2 with GS-11, O-3 with GS-12, O-4 with GS-13 and GM-13, and O-5 with GS-14 and GM-14.

Five variables apply only to military officers. Dummy variable ACAD, indicates whether the subject is a graduate of one of the three military service academies. COMM assigns a 0 to officers with reserve commissions and a 1 to officers with regular commissions. AERO distinguishes pilots and navigators from officers without aeronautical ratings. The Total Active Federal Military Service Date is subtracted from class entry date to get STIM, or service time. Likewise, the Total Active Federal Commissioned Service Date is used to calculate commissioned time, CTIM.

The first of six variables concerning undergraduate experience is UDEG, which distinguishes between Bachelor of

Arts and Bachelor of Science degrees. The time since undergraduate degree receipt is measured by DTIM. The other undergraduate variables are MAJ, UGPA, RATE, and RATGPA, defined below.

MAJ is a three-way, interval indicator of the technical degree of the undergraduate major. To be eligible for the GLM option, the candidate may have practically any undergraduate major. Yet the GLM curriculum includes several courses of a rather technical nature, including Statistics, Quantitative Decision Making, and Reliability (6:170-171). It is reasonable to assume that students with non-technical backgrounds might struggle in technical graduate courses. Appendix C lists the undergraduate majors assigned to the three categories in MAJ: non-technical, semi-technical, and technical.

UGPA stands for undergraduate grade point average, the familiar average of numerically converted course grades weighted for course credit hours. The intended operational definition of UGPA is the grade average, measured on a four point scale, of all courses taken for credit at the institution granting the undergraduate degree. Excluded are courses granting grades of "incomplete," "withdrawal," "pass," and "fail;" courses taken at other than the degree-granting school; and course credit obtained through examination. Due to limited time for data collection, I can not calculate every GGPA independently. A final grade average printed on a transcript will be recorded as UGPA

after a cursory check of its compliance with the operational definition. Unfortunately, grading systems and methods vary from school to school, and UGPA must be suspected for low reliability.

RATE indicates degree of admissions competitiveness at the institution granting the undergraduate degree. Appendix D summarizes the admissions standards imposed by schools listed under each of six categories of admissions competitiveness (2:vii). Appendix E lists the institutions in their appropriate categories. The ratings are based on admissions test scores and high school grades of the college freshman class of 1981-1982 only. Reliability of RATE is thus limited, as a contemporary competitiveness rating is not available for those who graduated well before or well after 1982.

RATGPA is simply the product of RATE and UGPA. It may be thought of as the undergraduate GPA adjusted for the competitiveness of the institution. Hopefully, this variable will compensate for nonstandard performance assessment among many schools of varying degrees of difficulty.

One indication of the technical orientation of students is their scholastic math record. Imagine a GLM student whose only undergraduate math experience was a C grade in one College Algebra Course 15 years ago. How would this student fare in an AFIT Quantitative Decision Making course, covering linear programming and queueing theory, given competition from classmates who have taken Calculus through Differential

Equations? In an attempt to measure differences in math backgrounds, MATH, MATG, and MATT are included in the study.

MATH is the total number of undergraduate and graduate semester hours of math and statistics for which passing grades were earned at any institution. MATG is the math GPA or the average math or statistics course grade, weighted for the number of course semester hours. MATT measures time since math, and is the average elapsed time from the date of course completion to AFIT class entry, weighted for the number of course semester hours. A desirable fourth variable would identify the average course difficulty, for example, rating College Algebra as low difficulty and Differential Equations as high difficulty. Such a variable can not reliably be constructed, however, due to limited information given in one-line, frequently abbreviated course titles on college transcripts.

Candidates for the GLM option must submit scores of either the GMAT or the GRE, but few students take both tests. GREV, GREQ, and GREA are the scores on the verbal, quantitative, and analytical subtests, respectively, of the General Test of the GRE. The lowest obtainable score on each of these tests is 200, and the highest is 800. GRET is the sum of GREV and GREQ. National average reliabilities for the verbal, quantitative, and analytical subtests have ranged from .88 to .96 on recent editions (13:24).

GMAV, GMAQ, and GMAT are the verbal, quantitative, and total scores of the Graduate Management Admission Test.

Verbal and quantitative scores range from 0 to 60, and total scores range from 200 to 800. These scores are not directly comparable with scores of the GRE (11:14).

Two variables reflect previous graduate work. GDEG indicates whether the subject earned a master's degree before entering AFIT. GHRS defines the number of graduate semester hours earned before AFIT. These two predictors should be highly correlated.

GGPA, of course, is the criterion variable. It is calculated by the AFIT administration uniformly for all students who eventually graduate. GGPA does not average in grades for undergraduate review courses nor grades for satisfactory/unsatisfactory courses.

The motivation survey (Appendix F) can only be administered conveniently to the currently resident GLM 89S class. The two motivation variables drawn from the survey will not be included in the regression study, since the smaller motivation sample size would draw down the sample size for the entire regression. ACHS and ACHW may, however, be demonstrative in the correlation study. Both variables indicate the need for achievement (28:251-266)--ACHS in the AFIT academic environment, and ACHW in the environment of Air Force work in general. Each variable is calculated as the mean of the responses to the corresponding set of five survey items. An interval measurement scale is assumed to be appropriate.

Model Development

The first research objective, MLR model development, will be accomplished with the statistical software package known as SAS (Statistical Analysis System), which is resident on the AFIT VAX minicomputer. A number of SAS procedures, or PROC's, will prove helpful. Model development involves four sequential steps described below: correlation analysis, predictor selection, model refinement, and residual analysis.

Correlation Analysis. This first step in model development investigates the interrelationships between model variables. Scatterplots will provide gross illustrations of relationships between GGPA and commonly used predictors. The SAS correlation procedure, PROC CORR (22:861), will calculate a matrix of sample correlation coefficients between every predictor/criterion pair and every predictor/predictor pair. This correlation matrix will point out promising predictors and possible sources of multicolliearity. PROC CORR will also calculate simple descriptive statistics for each variable, including the mean and the number of observations recorded.

Predictor Selection. The next step in model development is to select the subset of candidate predictor variables that collectively explain GGPA variance in the most efficient manner. Twenty-nine predictor variables are available for the regression, and the addition of each one to the model will increase the model's coefficient of determination, $R^2$. However, it is better to be parsimonious with predictors

included in the regression (3:162), as too many can cloud our understanding of the model. The procedure used here to select the "best" set of predictors is commonly known as stepwise regression.

PROC STEPWISE will perform this analysis (23:763). This method begins by fitting a least squares model with no predictor variables, the so-called "reduced" model (19:87-89). It then creates a "full" model by adding a predictor varaible and its least squares coefficient to the reduced model. For this step, STEPWISE calculates an F statistic to test the null hypothesis that the true value of the added variable's coefficient is 0. The F statistic is calculated as

$$F = \frac{(SSE_{reduced} - SSE_{full}) / (k - g)}{MSE_{full}} \qquad (2)$$

where

$SSE_{reduced}$ = sum of squares error of reduced model
$SSE_{full}$ = sum of squares error of full model
$MSE_{full}$ = mean square error of full model
$k$ = number of predictor variables in full model
$g$ = number of predictor variables in reduced model

One by one, each predictor is added to the reduced model, and an F statistic is calculated for each. The predictor that produces the largest F is the one added to the model for this step, provided its F is statistically significant at the .10 level. The process is repeated, this time taking the full model of the previous step to be the

reduced model of the current step. This adds another predictor to the growing model if its F statistic is significant at .10. At this point, STEPWISE tests both included predictors for significance at .10 and eliminates any that are not significant. The process of variable additions and deletions ends when no variables outside the model are significant enough to enter and all variables in the model are significant enough to remain (23:764-765).

The solution of stepwise regression will be a single model with predictor variables guaranteed by the methodology to be significant at the .10 level. As an added measure, another criterion will be employed that could cause settlement on one of the models encountered enroute to the stepwise solution. Mallows' $C_p$ statistic is an estimate of a model's total squared error, which is the sum of a bias component and a random error component (5:86-88). When an MLR equation contains P - 1 predictor variables, the expected value of $C_p$ is P. Thus, bias may be minimized by selecting a model for which $C_p$ is approximately equal to P. On the other hand, bias should not be eliminated at the expense of higher total squared error, $C_p$. The absolute difference between $C_p$ and P will be determined for each step of the stepwise procedure. Model selection will minimize bias if not detrimental to total squared error.

Model Refinement. The third step in developing a model is refining the model resulting from stepwise regression. PROC REG will be used to examine plots of residuals versus

each predictor. A residual is the difference between an actual GGPA data value and the fitted value of GGPA obtained by substituting corresponding predictor values into the proposed model. A non-random pattern of points on the residual plot indicates a lack of fit, that is, an inappropriate model. In this case, the best subset of variables is at hand, but a better equation exists that may have higher powers or products of the current variables. The pattern of points plotted should offer some hint as to the proper adjustment to be made. If a dummy variable is included in the model, residual plots should be examined for each setting of the dummy (20:556-560).

Residual Analysis. This final step in model development is a validity check of the four assumptions required to make inferences with an MLR model. These assumptions were described in Chapter 2, but only with the refined model and the error terms it produces can the validity of the assumptions be ascertained. Again, PROC REG will be helpful.

The zero expectation assumption should hold if the best subset of predictors is selected and this model is properly refined. The constant variance assumption is tested by examining a plot of residuals versus predicted GGPA's. Points should be scattered randomly. The normality assumption is confirmed by an approximately normal histogram of the residuals (20:587) and studentized residuals falling primarily between -2 and 2 (24:337-340). The studentized residual is the residual divided by the standard error of the

residual. Finally, since observations will not be made at successive points in time, there is no reason to suspect that the independence assumption is invalid.

## Model Validation

The model developed as above will be the best fitting regression equation to the known GGPA data values used to build it. In order to use this model to predict future GGPA's, its validity must be checked with "future" data, that is, data not used to develop it. This is the second research objective. The model will be considered valid if, for predictor data of future subjects, it predicts GGPA values that are close to the actual GGPA's of future subjects.

For purposes of validation, the total number of subjects will be divided into two subsets: the model group and the validation group. The model group will consist of all 108 subjects in the GLM 86S, 87S, and 88S classes. Data of these subjects will be used to build the MLR model. The validation group will consist of all 32 subjects in the GLM 89S class. Data of this group will be used to calculate validation measures.

The measure of validity will be the root mean square error, RMSE, which is calculated as

$$RMSE = (SSE / N)^{1/2} \qquad (3)$$

where

N = number of subjects in GLM 89S

and

$$SSE = \Sigma \, [(GGPA_{actual} - GGPA_{predicted})^2] \tag{4}$$

Summary

This chapter discussed the plan for accomplishing the research. The method of data collection and manipulation was explained, and the population to be studied was identified. Thirty two variables were given operational definitions. Model development was proposed as a four step process using three procedures of the software package SAS. Finally, two measures of model validity were presented. The next chapter examines the results of the study.

## IV. Results

This chapter presents the results obtained by following the plan outlined in the previous chapter. Necessary deviations from the plan will be discussed in the appropriate sections below. The first section describes the data collected. The models developed are then presented, followed by validation results.

### Data Description

Data missing from students' academic files proved to be a significant problem. Missing values in the data set reduced the number of complete records on which analyses could be performed. So few TAFMSD's and TAFCSD's were found in academic files that an ATLAS data base search of all active duty Air Force officers' records was conducted to obtain the information.

Table 1 shows frequencies for indicator and dummy variable values. Table 2 describes the mean and variability of continuous variables. In both tables, the number of subjects, N, for which data was available is less than the total sample size of 140 for many variables. As expected, the mean values of UGPA, GRET, and GMAT are greater than the values considered minimal for eligibility: 2.5, 1000, and 500, respectively. However, minimum values observed are less than these cutoff criteria. This illustrates the flexibility with which Admissions has applied their various standards.

Table 1. Frequencies For Indicator and Dummy Variable Values

| Variable | N | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| SEX | 140 | female 27 | male 113 | --- | --- | --- | --- | --- |
| AF | 140 | no 39 | yes 101 | --- | --- | --- | --- | --- |
| NAVY | 140 | no 131 | yes 9 | --- | --- | --- | --- | --- |
| CIV | 140 | no 111 | yes 29 | --- | --- | --- | --- | --- |
| RANK | 140 | --- | 0-1 1 | 0-2/GS-11 34 | 0-3/GS-12 95 | 0-4/GS-13/ GM-13 9 | 0-5/GS-14/ GM-14 1 | --- |
| ACAD | 114 | no 96 | yes 18 | --- | --- | --- | --- | --- |
| COMM | 98 | reserve 37 | regular 61 | --- | --- | --- | --- | --- |
| AERO | 105 | no 83 | yes 22 | --- | --- | --- | --- | --- |
| UDEG | 140 | BA 25 | BS 115 | --- | --- | --- | --- | --- |
| MAJ | 140 | --- | non-technical 33 | semi-technical 78 | technical 29 | --- | --- | --- |
| RATE | 139 | --- | non competitive 11 | less competitive 27 | competitive 55 | very competitive 22 | highly competitive 6 | most competitive 18 |
| GDEG | 140 | no 108 | yes 32 | --- | --- | --- | --- | --- |

Table 2. Descriptive Statistics For Continuous Variables

| Variable | N | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| AGE | 138 | 31.831 | 4.206 | 24.600 | 44.400 |
| STIM | 99 | 8.154 | 3.861 | 2.200 | 19.400 |
| CTIM | 96 | 6.485 | 3.014 | 2.000 | 16.900 |
| DTIM | 140 | 7.788 | 3.831 | 0.400 | 21.000 |
| UGPA | 140 | 3.074 | 0.467 | 2.080 | 4.000 |
| RATGPA | 139 | 9.892 | 3.934 | 2.618 | 20.580 |
| MATH | 140 | 13.709 | 8.000 | 0.000 | 50.610 |
| MATG | 135 | 2.941 | 0.642 | 1.600 | 4.280 |
| MATT | 137 | 9.979 | 4.165 | 0.250 | 24.890 |
| GREV | 73 | 545.068 | 77.766 | 370.000 | 770.000 |
| GREQ | 73 | 613.013 | 92.761 | 360.000 | 770.000 |
| GREA | 63 | 591.904 | 108.922 | 370.000 | 800.000 |
| GRET | 73 | 1158.082 | 149.468 | 730.000 | 1460.000 |
| GMAV | 79 | 33.012 | 5.571 | 22.000 | 46.000 |
| GMAQ | 79 | 32.443 | 6.201 | 18.000 | 47.000 |
| GMAT | 79 | 548.367 | 69.041 | 420.000 | 700.000 |
| GHRS | 139 | 11.766 | 17.144 | 0.000 | 73.000 |
| GGPA | 140 | 3.635 | 0.230 | 3.066 | 4.000 |
| ACHS | 15 | 23.133 | 3.961 | 14.000 | 29.000 |
| ACHW | 15 | 25.933 | 2.186 | 20.000 | 29.000 |

Tables 1 and 2, along with the demographic report at Appendix G, provide a good overview of the GLM classes of 1986 through 1989.

## Models Developed

This section describes results of the four sequential steps of model development proposed in Chapter 3. These are correlation analysis, predictor selection, model refinement, and residual analysis. The entire data set (classes 86S-89S, N = 140) was used in correlation analysis. The development data set (classes 86S-88S, N = 108) was used for the rest of model development.

Correlation Analysis. The sample correlation coefficients, r, between all 31 predictor variables and GGPA are presented in Appendix H. For each value of r calculated, those records that did not have a data value for both variables being correlated were ignored. The number of records, N, used to calculate each r is listed in Appendix H. Also shown are the p-values, or significance levels, for the null hypothesis that the population correlation coefficient is actually 0.

The same information is repeated in Table 3 for the most highly correlated variables. ACHS and ACHW, the need for achievement in the AFIT and general Air Force environments, respectively, have the first and sixth largest correlations among all the predictors. Unfortunately, this is the only kind of information studied herein to which the AFIT

Admissions Division does not currently avail itself. ACHS and ACHW are less statistically significant than the other highly correlated predictors because of the much smaller sample size available for the motivation survey.

Table 3. Best Correlations, r, With GGPA

| Variable | N | p-value | r | Variable | N | p-value | r |
|---|---|---|---|---|---|---|---|
| ACHS | 15 | .0500 | .514 | ACHW | 15 | .0995 | .441 |
| GREQ | 73 | .0001 | .502 | RATE | 139 | .0001 | .371 |
| GRET | 73 | .0001 | .483 | GREV | 73 | .0045 | .329 |
| RATGPA | 139 | .0001 | .480 | GMAQ | 79 | .0032 | .328 |
| GMAT | 79 | .0001 | .454 | GREA | 63 | .0164 | .301 |
| GMAV | 79 | .0001 | .449 | UGPA | 140 | .0037 | .244 |

As expected, all scores of both the GRE and GMAT are among the highest correlates. RATGPA, the undergraduate GPA adjusted for the institution's admissions competitiveness, is fourth on the list and highly significant. Note that this constructed variable has nearly twice the correlation value of UGPA alone.

Appendix I graphically represents the correlations of various predictors with GGPA. The plots of GRET and RATGPA best portray linear relationships. At the other extreme, the AGE (r=-.106) plot is little more than a random scattering of points.

Predictor Selection. The first step in the SAS STEPWISE procedure is to eliminate from consideration all records for which data is missing from any of the candidate predictor variables. SAS was unable to execute STEPWISE for the

original data set because only one of 108 records contained a non-missing value for every variable. Two main causes were found for this problem.

The first cause for so much missing data was that five variables applied only to military officers or to Air Force officers. Using these variables in stepwise regression would eliminate from consideration the data of all 29 civilians. This course would be unsatisfactory, since the model was conceived as a tool for objectively deciding the eligibility of <u>all</u> candidates--officers and civilians. A decision was thus made to drop these five variables, namely, ACAD, COMM, AERO, STIM, and CTIM. Appendix H shows that correlation coefficients of these predictors were relatively small.

The second cause of missing data was that only 17 applicants took both the GRE and the GMAT. The effect of this fact alone is to reduce the number of records available to perform stepwise regression to 17. Since applicants may submit scores of either test, a predictive model should be able to use both kinds of information. On the other hand, a valid model can not be developed on the basis of only 17 records. The compromise made was to divide the development data set into two subsets upon which two models would be developed. The first data subset consisted of those 59 students of classes 86S through 88S who had taken the GRE. Using this data, a "GRE model" was subsequently developed that can be used to predict future GGPA's of GRE score submitters. The second data subset consisted of the 62

students of classes 86S through 88S who had taken the GMAT. The "GMAT model" developed from this data can be used to predict future GGPA's of those applicants who submit GMAT scores.

Sample size reduction was also avoided by substituting certain missing values with mean values. A total of 21 missing values in the variables GREA, GHRS, AGE, MATG, and MATT were replaced by their respective varible means.

Table 4 summarizes the stepwise regression for the GRE model. The last variable entered, RANK, decreased the model's total squared error, $C_p$, but also increased the absolute difference, $|C_p - P|$. Because the increase in absolute difference was deemed more significant than the reduction in $C_p$, RANK was not included in the subset of predictors selected for the GRE model.

Table 4. Summary Of STEPWISE Steps Toward GRE Model

| Step | Variable Entered | Variable Removed | P | Model $R^2$ | $C_p$ | $\|C_p - P\|$ | p-value for Variable |
|---|---|---|---|---|---|---|---|
| 1 | RATGPA | | 2 | 0.426 | 20.627 | 18.627 | .0001 |
| 2 | GRET | | 3 | 0.543 | 7.441 | 4.441 | .0004 |
| 3 | UGPA | | 4 | 0.569 | 6.028 | 2.028 | .0753 |
| 4 | MAJ | | 5 | 0.591 | 5.157 | 0.157 | .0965 |
| 5 | RANK | | 6 | 0.615 | 4.266 | 1.734 | .0897 |

Table 5 gives the steps taken toward the GMAT model. The last variable entered, a dummy variable, minimized both $C_p$ and $|C_p - P|$.

Table 5. Summary Of STEPWISE Steps Toward GMAT Model

| Step | Variable Entered | Variable Removed | P | Model $R^2$ | C(P) | $\lvert C_P - P \rvert$ | p-value for Variable |
|---|---|---|---|---|---|---|---|
| 1 | GMAV | | 2 | 0.395 | 42.553 | 40.553 | .0001 |
| 2 | RATGPA | | 3 | 0.493 | 28.384 | 25.384 | .0014 |
| 3 | NAVY | | 4 | 0.538 | 22.765 | 18.765 | .0197 |

Model Refinement. The models formed by STEPWISE involved only first order terms and no products of the selected variables. Residuals resulting from these models were plotted against each predictor variable in the model in order to check the appropriateness of the model. All such residual plots were random scatterings of points, indicating the models offer adequate fits to the data.

Table 6 shows the results of analysis of variance on the GRE model. The model's coefficient of determination, $R^2$, is quite good. Adjusting $R^2$ for chance sampling error (15:230-231) reduces the figure only slightly. Successful results are probably due to the two strategies employed to select a study population and discussed in Chapter 3: process uniformity and input variation.

Table 6. Analysis Of Variance For GRE Model

Model $R^2$ = 0.5914     Model Adjusted $R^2$ = 0.5606

| Source | Degrees Freedom | Sum of Squares | Mean Square | F | Model p-value |
|---|---|---|---|---|---|
| Model | 4 | 1.73473446 | 0.43368361 | 19.180 | 0.0001 |
| Error | 53 | 1.19838556 | 0.02261105 | | |
| Total | 57 | 2.93312002 | | | |

The GRE model is defined in Table 7 in terms of parameter estimates or β's for the four predictor variables and the constant intercept. Each variable's p-value is the level of significance for the null hypothesis that the variable has no predictive power over and above that provided by the other predictors in the model. Tolerance, which ranges from 0 to 1 by definition, would be nearly zero if the corresponding predictor were highly correlated with one or more of the other included predictors (20:492). Tolerance values close to 1 indicate efficiency of the GRE model, with little overlap of predictive power among the variables.

Table 7. Parameter Estimates For GRE Model

| Variable | Degrees Freedom | Parameter Estimate | Variable p-value | Tolerance |
|---|---|---|---|---|
| INTERCEP | 1 | 2.39398287 | 0.0001 | |
| MAJ | 1 | 0.0433321 | 0.0965 | 0.98534868 |
| UGPA | 1 | 0.08700366 | 0.0474 | 0.97104322 |
| GRET | 1 | 0.0005428719 | 0.0006 | 0.87919109 |
| RATGPA | 1 | 0.02615774 | 0.0001 | 0.88764150 |

Analysis of variance results for the GMAT model are presented in Table 8. $R^2$ values are smaller than those for the GRE model but are still impressive. Table 9 lists the parameter estimates for the GMAT model. Again, large tolerance values suggest an efficient model.

Table 8. Analysis Of Variance For GMAT Model

Model $R^2$ = 0.5384 Model Adjusted $R^2$ = 0.5145

| Source | Degrees Freedom | Sum of Squares | Mean Square | F | Model p-value |
|---|---|---|---|---|---|
| Model | 3 | 1.88899570 | 0.62966523 | 22.546 | 0.0001 |
| Error | 58 | 1.61984340 | 0.02792833 | | |
| Total | 61 | 3.50883910 | | | |

Table 9. Parameter Estimates For GMAT Model

| Variable | Degrees Freedom | Parameter Estimate | Variable p-value | Tolerance |
|---|---|---|---|---|
| INTERCEP | 1 | 2.63925647 | 0.0001 | |
| NAVY | 1 | 0.17314384 | 0.0197 | 0.98948714 |
| GMAV | 1 | 0.02401282 | 0.0001 | 0.88278886 |
| RATGPA | 1 | 0.02171028 | 0.0007 | 0.88664514 |

It is interesting to study the predictors entered into these models. Several variables with large individual correlations with GGPA appear in the equations, but other high correlates did not enter. Apparently, high correlates such as GREQ and GMAT were so correlated with predictors already entered that their addition to the model would be largely redundant. On the other hand, MAJ and NAVY, two predictors with small values of r, did enter. This suggests that candidate predictors for a predictor selection procedure should not be chosen on the basis of individual correlation coefficients alone.

Residual Analysis. The validity of MLR assumptions was checked by examining the behavior of residuals for each

model. The zero expectation assumption was confirmed in the refinement step when examination of residuals plotted against each predictor revealed that the current models offered good fits to the data.

The constant variance assumption was checked with the plots of residuals versus fitted GGPA's appearing in Figures 1 and 2. Both graphs indicate that the variance of residuals decreases with larger fitted GGPA's. A similar pattern was not noticed, however, on plots of residuals versus predictors. If the variance of error terms is not constant, the parameter estimates obtained through ordinary least squares will not be distributed with the smallest possible variance (19:131-136). One solution to non-constant variances is the weighted least squares procedure, which can not be applied unless it is known how the error variance varies with predictor variables. Since no pattern was readily discernible from residual versus predictor plots, weighted least squares can not be employed. The otherwise very successful models will have to be accepted with the understanding that their $\beta$'s are not minimum variance estimators.

In his 1988 AFIT regression study, Prokopyk (21:33-34) encountered this same reduction in residual variance with increasing GGPA. He chose to compensate for this effect by transforming GGPA data as

$$GGPA = -[LOG(4.0 - GGPA + \delta)] \tag{5}$$

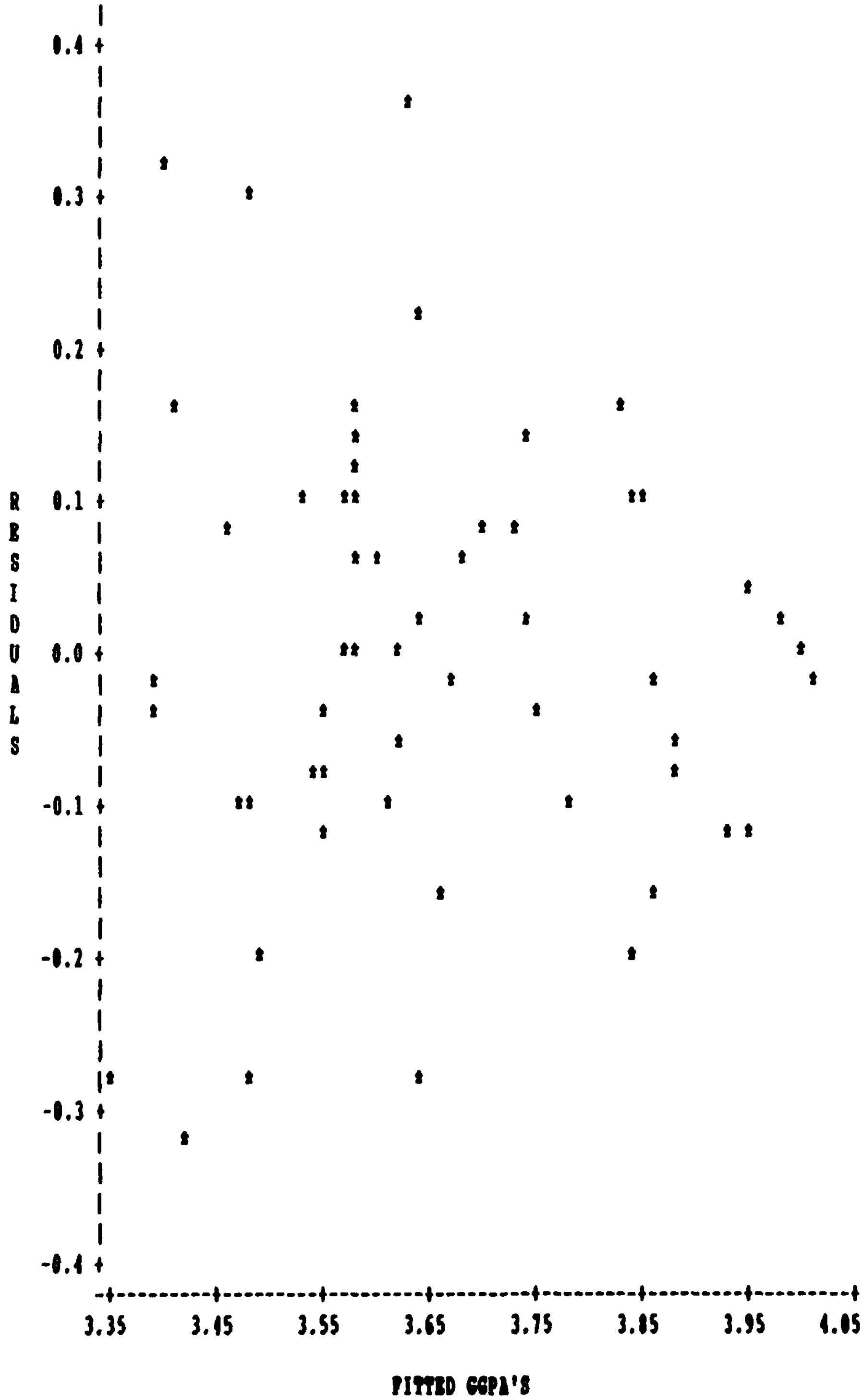



Figure 1. Residuals Versus Fitted GGPA's For the GRE Model

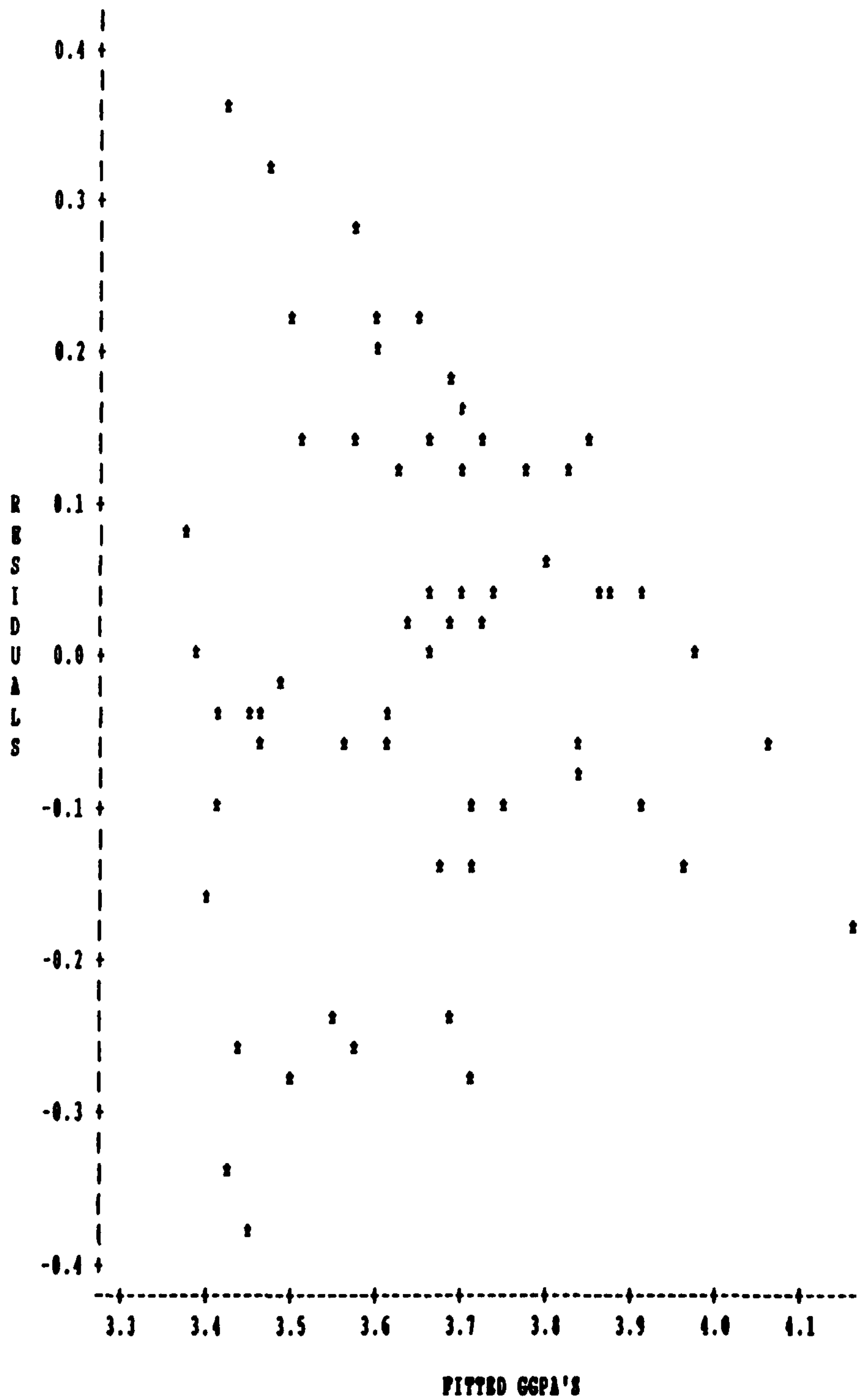



Figure 2. Residuals Versus Fitted GGPA's For the GMAT Model

where $\delta$ is a correction factor. Through trial and error, he determined the value of $\delta$ for which variances were equalized among the predictors. Prokopyk then tested the first and second moment specification to determine if the unequal variances significantly affected the regression model. He concluded that there was no significant advantage to logarithmic transformation.

The normality assumption was confirmed for each model with a roughly normal frequency distribution of residuals. Also, most of the studentized residuals listed in Appendix J and Appendix K range from -2 to 2. There is no reason to suspect the independence assumption might be invalid.

## Validation Results

Data of the validation group of 32 GLM 89S students was used to validate both models. The errors of prediction in terms of the root mean square errors are 0.2269 for the GRE model and 0.2842 for the GMAT model. These numbers are small enough to validate both models.

The predicted GGPA output from these models is a point estimate. The probability that the actual GGPA will exactly match the predicted GGPA is zero. However, a prediction interval of GGPA values can be constructed with width proportional to the probability that the predicted GGPA will fall within. Appendix J and Appendix K give the lower and upper boundaries of the 95% prediction intervals of the models. One can be 95% certain that an applicant, for whom

the model predicts a certain GGPA, would actually receive a GGPA within the boundaries of the corresponding prediction interval. The average interval width for the GRE model is 0.629, while the average interval width for the GMAT model is 0.679.

## Summary

This chapter presented the results obtained for this investigation. The data was summarized and described, as a demographic portrait of the GLM classes of 1986 to 1989 was provided. Problems caused by missing data were described as the reason for developing two models, one for students with GRE scores and one for students with GMAT scores. Both models were validated for future use.

# V. Conclusion

This final chapter provides both logical and subjective interpretations of the results and the entire research project. The first section summarizes key results of the study. Next, possibilities for additional research are suggested, followed by a discussion of policy implications for management. The last section gives some broad lessons learned about regression studies.

## Key Results

The most important result is that the $R^2$ values for the GRE model and the GMAT model were relatively impressive, .59 and .54, respectively. Large coefficients of determination probably result from a combination of three factors. First, process uniformity was ensured by limiting the studied population to only one curriculum group of AFIT students who had all taken essentially the same series of courses. Hence all subjects were processed uniformly through the same educational system, making the job of modeling that system much easier. Another possible reason for large $R^2$ values is that input variation was maximized with the choice of the GLM students as subjects. The tremendous variation of input factors among GLM students provides excellent potential for explanation of GGPA variation. Finally, a new predictor, RATGPA, was introduced as the product of an undergraduate admissions competitiveness rating and UGPA. Multiplying UGPA

by RATE nearly doubled UGPA's correlation with GGPA. Furthermore, Stepwise regression entered RATGPA into the GRE model first and the GMAT model second.

The need for achievement was found to be highly correlated with GGPA. The small sample size of GLM 89S students who responded to the motivation survey precluded the use of n-Ach in the regression study.

Although considerable data collection effort was required to develop three variables describing the undergraduate math experience, these variables did not enter the regression equations. After first failing to enter, all two- and three-factor products of the basic math variables were offered as potential regressors. Again, no math variable significantly explained variation in GGPA. This is surprising, but it points out a valuable lesson about MLR: the results of a predictor selection process are often counterintuitive due to correlation among the various predictors.

## Recommendations For Further Research

The current research could be followed-up in several areas. First and foremost, the problem of non-constant variance could be corrected. Both the GRE model and the GMAT model violated the constant variance assumption. A well known transformation exists for equalizing variances; Prokopyk (21:33-34) found it useful in his AFIT prediction

study. This method could be employed to improve the GRE and GMAT models.

The correlation between motivation, especially n-Ach, and GGPA should be studied at length. A larger sample size must be accumulated before n-Ach can be used for regression.

Local validity studies will always be required when predictive models are used. The GRE and GMAT models were validated with validation groups of only 17 and 14 students, respectively. Although the RMSE was considered satisfactory, larger validation groups in the future would further substantiate the models' validities.

With regard to methodology, I strongly recommend that future researchers match their statistical tools to the nature of the work. If done properly, MLR is an iterative procedure involving predictor selection, model refinement, residual analysis, and validation. SAS interactive modes greatly facilitate rapid model changes and data visualization required in MLR, whereas the batch mode is relatively slow and cumbersome.

## Policy Implications For Management

This study has shown that motivation is highly correlated with GGPA. Since people who take the initiative to apply for AFIT admission are understandably assumed to be more motivated than "centrally identified" officers, Admissions should continue to give preferential treatment to applicants.

If the Admissions Division were to adopt a GGPA predictive model, the eligibility determination for an applicant could be made simply by comparing his or her predicted GGPA to a predetermined minimum acceptable GGPA. As budgets and student quotas change, the cut-off GGPA could be raised or lowered as needed to yield the desired number of eligibles.

Predicting academic success at AFIT is a difficult but important job. Both the Air Force and unsuccessful student incurr considerable costs of failure. The Admissions Division currently determines academic eligibility by subjectively assessing applicants' records. This requires a great deal of time and energy of highly trained admissions counselors. With today's emphasis on streamlining operations, Admissions would be well served by statistical models in place of subjective assessments.

## Appendix A: Data Collection Sheet

SSAN ____________________ Name ______________________

Class _________ Branch ___________ Gender ____________

GGPA _______ Birthdate ___________ Rank/Grade _________

TAFMSD _________________ TAFCSD ______________________

Aero rating ____________ Academy Graduate _____________

UG school granting degree ______________________________

UG degree _______ Major ________________________________

UGPA ____________ UG degree date ______________________

Previous graduate degree ______ Graduate hours _________

GRE-V _________ GMAT-V __________
GRE-Q _________ GMAT-Q __________
GRE-T _________ GMAT-T __________
GRE-A _________ Date __________
Date _________

### Math Courses

| Course title | # Semester hours | Grade | Date |
|---|---|---|---|

## Appendix B: Key to the Database

| Variable Name | Description |
|---|---|
| RCRD | record number (0-140) |
| COMM | commission type<br>0 = reserve<br>1 = regular |
| CLAS | year of graduation (86-89) |
| AF | 0 = not Air Force officer<br>1 = Air Force officer |
| NAVY | 0 = not Naval officer<br>1 = Naval officer |
| CIV | 0 = not civilian<br>1 = civilian |
| GGPA | AFIT graduate GGPA (4 point scale) |
| SEX | gender<br>0 = female<br>1 = male |
| RANK | officer rank / civilian grade<br>1 = O-1 / GS-10<br>2 = O-2 / GS-11<br>3 = O-3 / GS-12<br>4 = O-4 / GS-13, GM-13<br>5 = O-5 / GS-14, GM-14 |
| AERO | aeronautical rating<br>0 = none<br>1 = pilot, navigator, other rated |

| | |
|---|---|
| ACAD | 0 = not service academy graduate<br>1 = service academy graduate |
| UDEG | undergraduate degree<br>0 = Bachelor of Arts<br>1 = Bachelor of Science |
| MAJ | technical degree of undergraduate major<br>1 = non-technical<br>2 = semi-technical<br>3 = technical<br>(see Appendix C) |
| UGPA | undergraduate GPA (4 point scale) |
| GREV | Graduate Record Exam - Verbal score |
| GREQ | Graduate Record Exam - Quantitative score |
| GRET | Graduate Record Exam - Total score |
| GREA | Graduate Record Exam - Analytical score |
| GMAV | Graduate Management Admission Test<br>Verbal score |
| GMAQ | Graduate Management Admission Test<br>Quantitative score |
| GMAT | Graduate Management Admission Test<br>Total score |

| | |
|---|---|
| GDEG | 0 = does not have previous graduate degree<br>1 = has previous graduate degree |
| GHRS | number of previous graduate semester hours |
| AGE | age in years |
| STIM | time since entering active duty in years |
| CTIM | time since commissioning in years |
| DTIM | time since earning undergraduate degree in years |
| RATE | degree of admissions competitiveness (see Appendix D and Appendix E) |
| ACHS | need for achievement at AFIT |
| ACHW | need for achievement in Air Force in general |
| MATH | semester hours of math and statistics |
| MATG | math and statistics GPA |
| MATT | average time since math and statistics |
| RATGPA | RATE x UGPA |

## Appendix C: Undergraduate Majors As Coded For the Variable MAJ

MAJ = 1
Non-technical

---

Advertising
Communication
Criminal Justice
Education
Elementary Education
English
Health and Physical Education
History
Industrial and Vocational Educational
International Affairs
Journalism
Philosophy
Political Science
Professional and Liberal Studies
Secondary Education
Special Education

MAJ = 2
Semi-Technical

---

Accounting
Aerospace Flight Technology
Agriculture
Aviation Management
Business Administration
Environmental planning
General Business
General Studies
Geography
Geology
Human Resources Management
Industrial Illustration
Industrial Technology
Logistics Management
Management
Marketing
Natural Resources
Psychology
Resources Management
Sociology

MAJ = 3

Technical

---

Aeronautics
Biochemistry
Biology
Chemistry
Computer Science
Engineering
Engineering Mechanics
Engineering Technology
Mathematics
Operations Research
Physics
Wood Science and Technology

## Appendix D: Admissions Standards For Each Value of RATE

### Barrons' Ratings of Admissions Competitiveness[1]

| CATEGORY | HS CLASS RANK | HS GPA | MEDIAN SAT SCORE | MEDIAN ACT SCORE | SELECTION RATIO | RATE |
|---|---|---|---|---|---|---|
| MOST COMPETITIVE | 10-20% | A to B+ | 625-800 | >27 | <1/3 | 6 |
| HIGHLY COMPETITIVE | 20-35% | B+ to B | 575-625 | 26-27 | 1/3 - 1/2 | 5 |
| VERY COMPETITIVE | 35-50% | no less than B- | 525-575 | 23-25 | 1/2 - 3/4 | 4 |
| COMPETITIVE | 50-65% | some req B- others C+ or C | 450-525 | 19-22 | 75% - 85% | 3 |
| LESS COMPETITIVE | top 65% | below C | below 450 | below 19 | >85% | 2 |
| NON-COMPETITIVE | evidence of HS graduation | ------ | not required for admission | not required for admission | [2] | 1 |

[1] This table is compiled from information provided in Barrons' Profiles of American Colleges (1).

[2] Most of these schools will admit applicants limited only by capacity.

## Appendix E: Undergraduate Institutions Represented, RATE, and Number of Graduates

| Undergraduate Institution | RATE | Number |
|---|---|---|
| Auburn U., AL | 3 | 1 |
| Barry U., FL | 3 | 1 |
| Baylor U., TX | 4 | 1 |
| Boston U., MA | 4 | 1 |
| Bowling Green State U., OH | 3 | 1 |
| Brigham Young U., UT | 3 | 1 |
| California State U./Chico, CA | 3 | 1 |
| California State U./Long Beach, CA | 4 | 1 |
| California State U./Sacramento, CA | 3 | 2 |
| Central State U., OH | 1 | 1 |
| Chaminade U. of Honolulu, HI | 3 | 1 |
| Chapman College, CA | 3 | 1 |
| Colorado State U.,CO | 3 | 1 |
| Columbus College, GA | 2 | 1 |
| Drury College, MO | 3 | 1 |
| East State Texas State U., TX | 2 | 1 |
| Eastern Illinois U., IL | 3 | 1 |
| Edinboro State College, PA | 2 | 1 |
| Florida State U., FL | 3 | 3 |
| Glassboro State College, NJ | 3 | 1 |
| Illinois State U., Il | 3 | 1 |
| Indiana State U., IN | 1 | 1 |
| James Madison U., VA | 4 | 1 |
| Judson College, AL | 2 | 1 |
| Kalamazoo College, MI | 5 | 1 |
| Kent State U., OH | 3 | 1 |
| Lane College, TN | 2 | 1 |
| Louisiana State University, LA | 1 | 1 |
| Manhatten College, NY | 3 | 2 |
| Michigan State U., MI | 3 | 1 |
| Moorhead State U., MN | 3 | 1 |
| New Mexico State U., NM | 2 | 1 |
| North Carolina State U., NC | 3 | 2 |
| Northern Arizona U., AZ | 3 | 1 |
| Ohio State U., OH | 1 | 3 |
| Ohio U., OH | 3 | 1 |
| Oregon State U., OR | 3 | 1 |
| Pacific Lutheran U., WA | 4 | 1 |
| Park College, MO | 2 | 2 |
| Parks College of St. Louis, IL | 3 | 2 |
| Parsons School of Design, NY | -- | 1 |
| Pennsylvania State U./U. Park Campus, PA | 4 | 2 |
| Perdue U./West Lafayette, IN | 3 | 1 |
| Rose-Hulman Institute of Technology, IN | 5 | 1 |
| Rutgers U./Rutgers College,NJ | 4 | 1 |

| | | |
|---|---|---|
| Saginaw Valley State College, MI | 2 | 1 |
| Siena College, NY | 4 | 1 |
| Slippery State College, PA | 2 | 1 |
| South Carolina State College, SC | 2 | 1 |
| South Dakota State U., SD | 3 | 2 |
| Southern Illinois U. at Carbondale, IL | 3 | 2 |
| State U. of New York at Albany, NY | 4 | 1 |
| State U. of New York at Geneseo, NY | 4 | 1 |
| State U. of New York at Stony Brook, NY | 4 | 1 |
| State U. of New York/College at Buffalo, NY | 3 | 1 |
| Texas Tech U., TX | 2 | 1 |
| Troy State U., AL | 2 | 2 |
| US Air Force Academy, CO | 6 | 17 |
| US Naval Academy, MD | 6 | 1 |
| U. of Akron, OH | 2 | 1 |
| U. of California/Riverside, CA | 4 | 1 |
| U. of California/Santa Cruz, CA | 4 | 1 |
| U. of Central Florida, FL | 3 | 1 |
| U. of Cincinnati, OH | 3 | 2 |
| U. of Dayton, OH | 3 | 1 |
| U. of Florida, FL | 4 | 2 |
| U. of Hawaii at Manoa,HI | 3 | 1 |
| U. of Idaho, ID | 1 | 2 |
| U. of Kentucky, KY | 3 | 1 |
| U. of Louisville, KY | 3 | 1 |
| U. of Maine at Orono, ME | 3 | 1 |
| U. of Maryland/College Park, MD | 3 | 2 |
| U. of Massachusetts at Boston, MA | 3 | 2 |
| U. of Michigan/Ann Arbor, MI | 5 | 1 |
| U. of Minnesota/Twin Cities, MN | 3 | 1 |
| U. of Missouri/ St. Louis, MO | 3 | 1 |
| U. of Nebraska at Omaha, NE | 1 | 2 |
| U. of New Mexico, NM | 2 | 1 |
| U. of North Carolina at Chapel Hill, NC | 4 | 1 |
| U. of Oklahoma, OK | 3 | 1 |
| U. of Pittsburg, PA | 4 | 1 |
| U. of South Carolina, SC | 3 | 1 |
| U. of Southern Colorada, CO | 1 | 1 |
| U. of Southern Mississippi, MS | 2 | 1 |
| U. of Texas at Arlington, TX | 3 | 1 |
| U. of Texas, Austin, TX. | 4 | 2 |
| U. of Utah, UT | 3 | 1 |
| U. of Virginia, VA | 5 | 3 |
| U. of Wisconsin/Madison, WI | 3 | 1 |
| Villanova U., PA | 4 | 1 |
| Virginia Polytechnic Institute & State U., VA | 4 | 1 |
| Wayland Baptist U., TX | 2 | 1 |
| Weber State College, UT | 2 | 5 |
| Western Carolina U., NC | 2 | 1 |
| Widener College, PA | 3 | 1 |
| Wright State U., OH | 2 | 3 |

## Appendix F: Motivation Survey

IMPORTANT POINT: Identification by name of each respondent is critcal for my analysis, although your names will not be included in the thesis report. Repeating, readers of the thesis will not be able to identify specific individuals. Individual responses will not be provided to management or to any other agency.

INSTRUCTIONS: Listed below are five statements that describe various things people do or try to do on their jobs. Please respond to each of the five items by describing your work attitudes from two perspectives: 1) as an AFIT student; and 2) in your Air Force work in general. Simply fill in both blanks for each item with the appropriate numbers from the scale listed below. Remember, there are no right or wrong answers.

| | |
|---|---|
| 1 = Never | 5 = Usually |
| 2 = Almost never | 6 = Almost always |
| 3 = Seldom | 7 = Always |
| 4 = Sometimes | |

1.) I do my best work when my job assignments are fairly difficult.

AFIT ____________ Air Force in general ____________

2.) I try very hard to improve on my past performance at work.

AFIT ____________ Air Force in general ____________

3.) I take moderate risks and stick my neck out to get ahead at work.

AFIT ____________ Air Force in general ____________

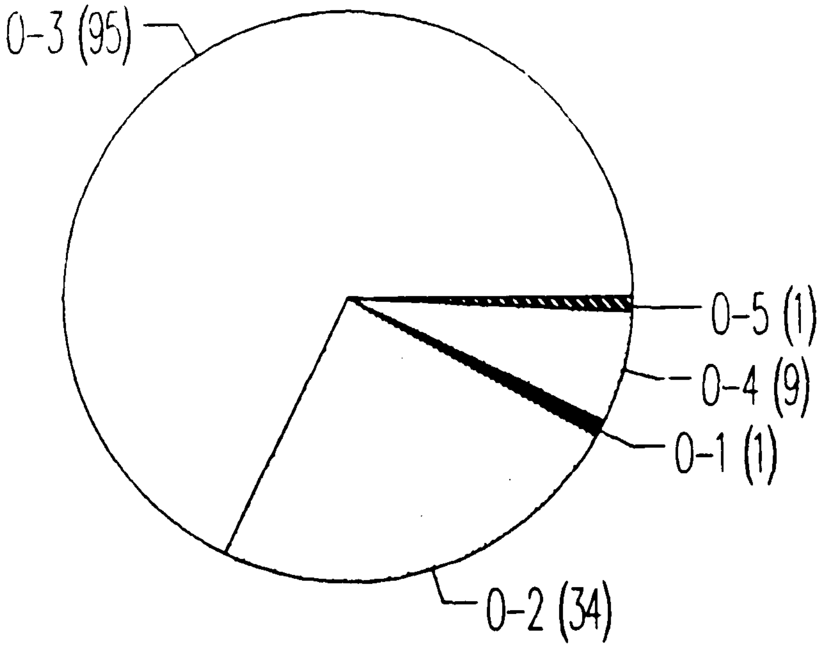
4.) I try to avoid any added responsibilities on my job.

AFIT ____________ Air Force in general ____________

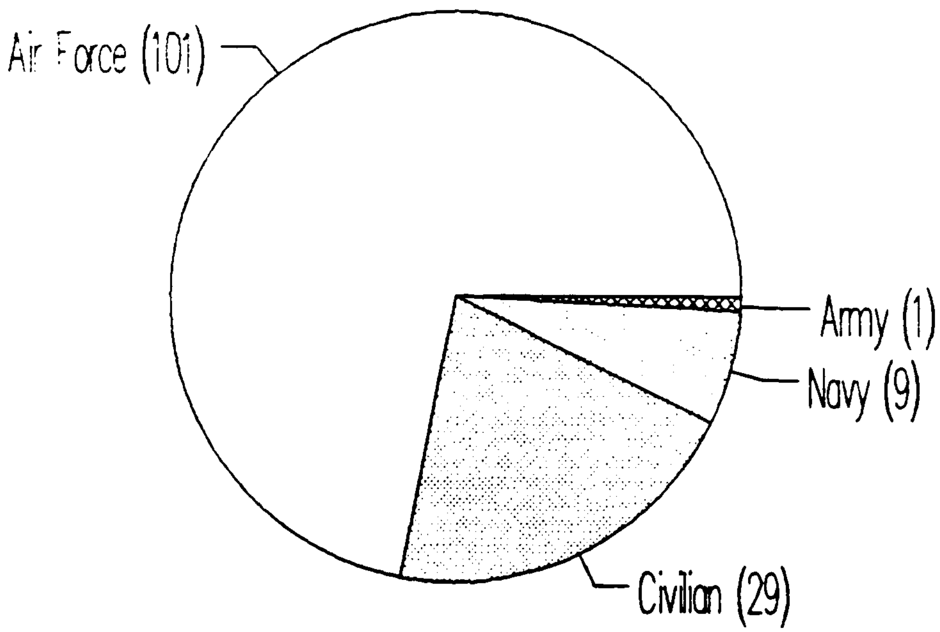
5.) I try to perform better than my co-workers.

AFIT ____________ Air Force in general ____________

# Rank (Including Civilian Equivalent)
## GLM 86S-89S



# Services Represented
## GLM 86S–89S



# UG Majors
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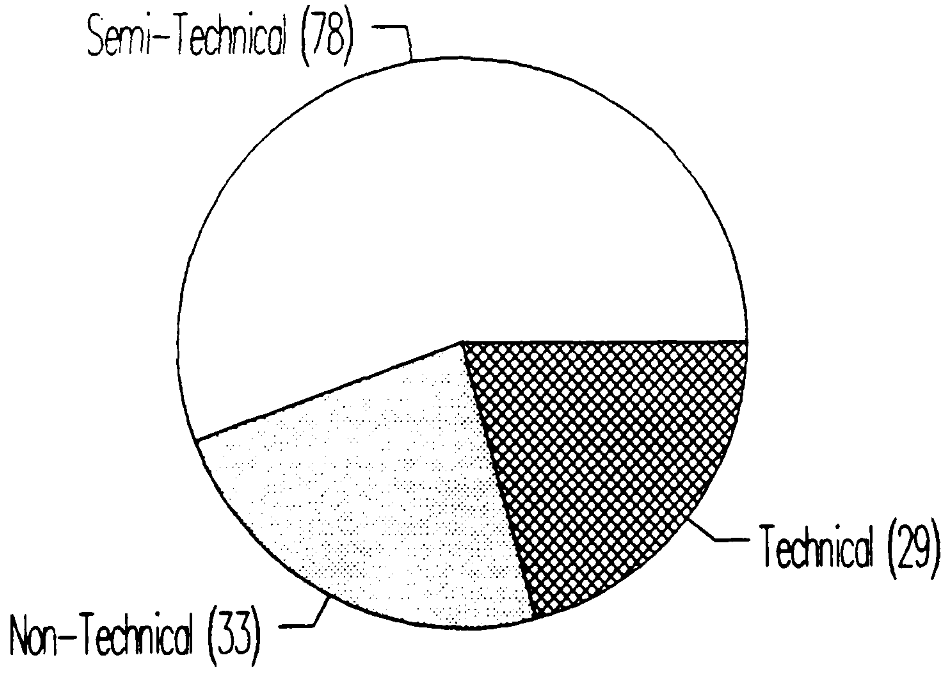
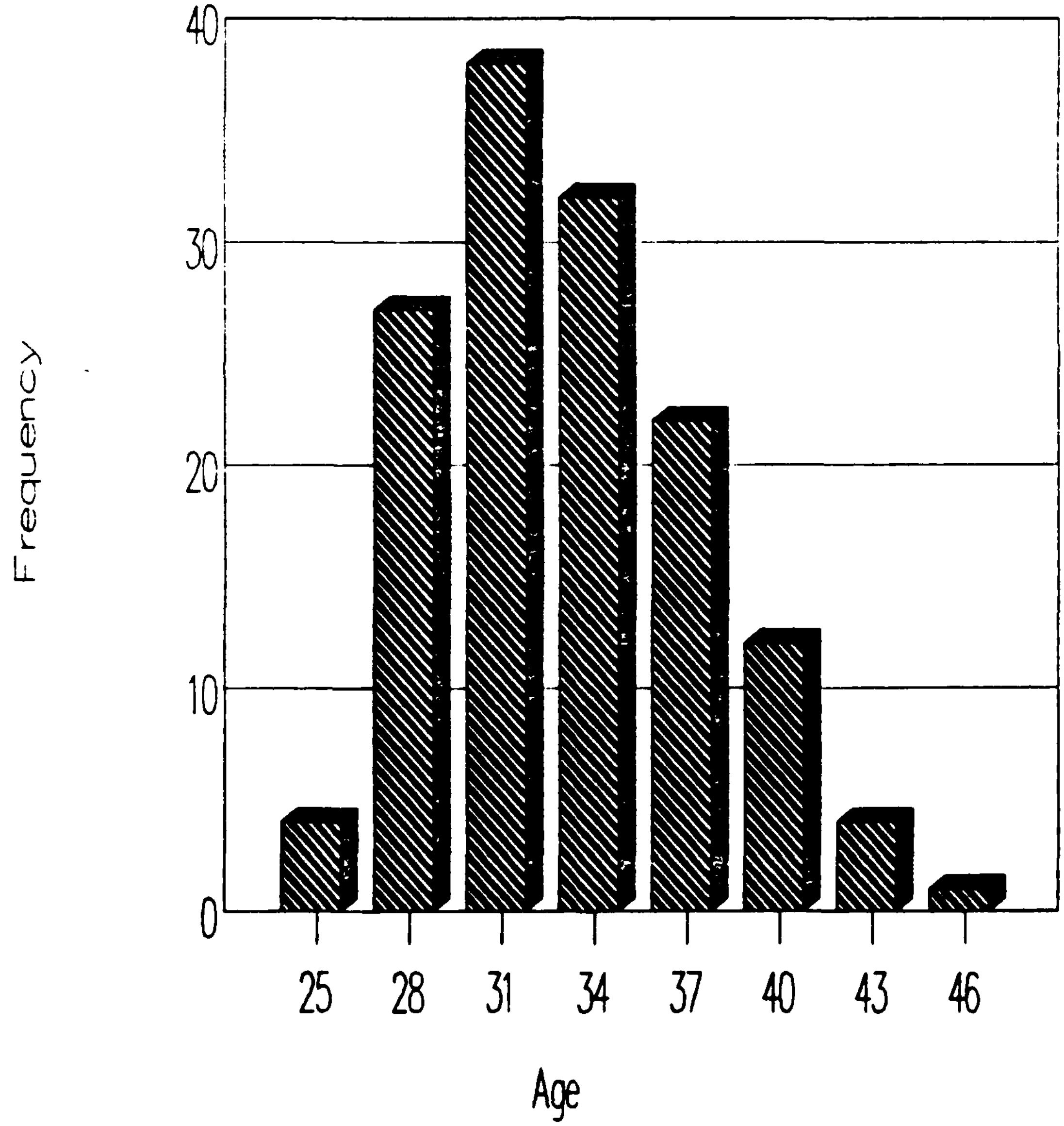


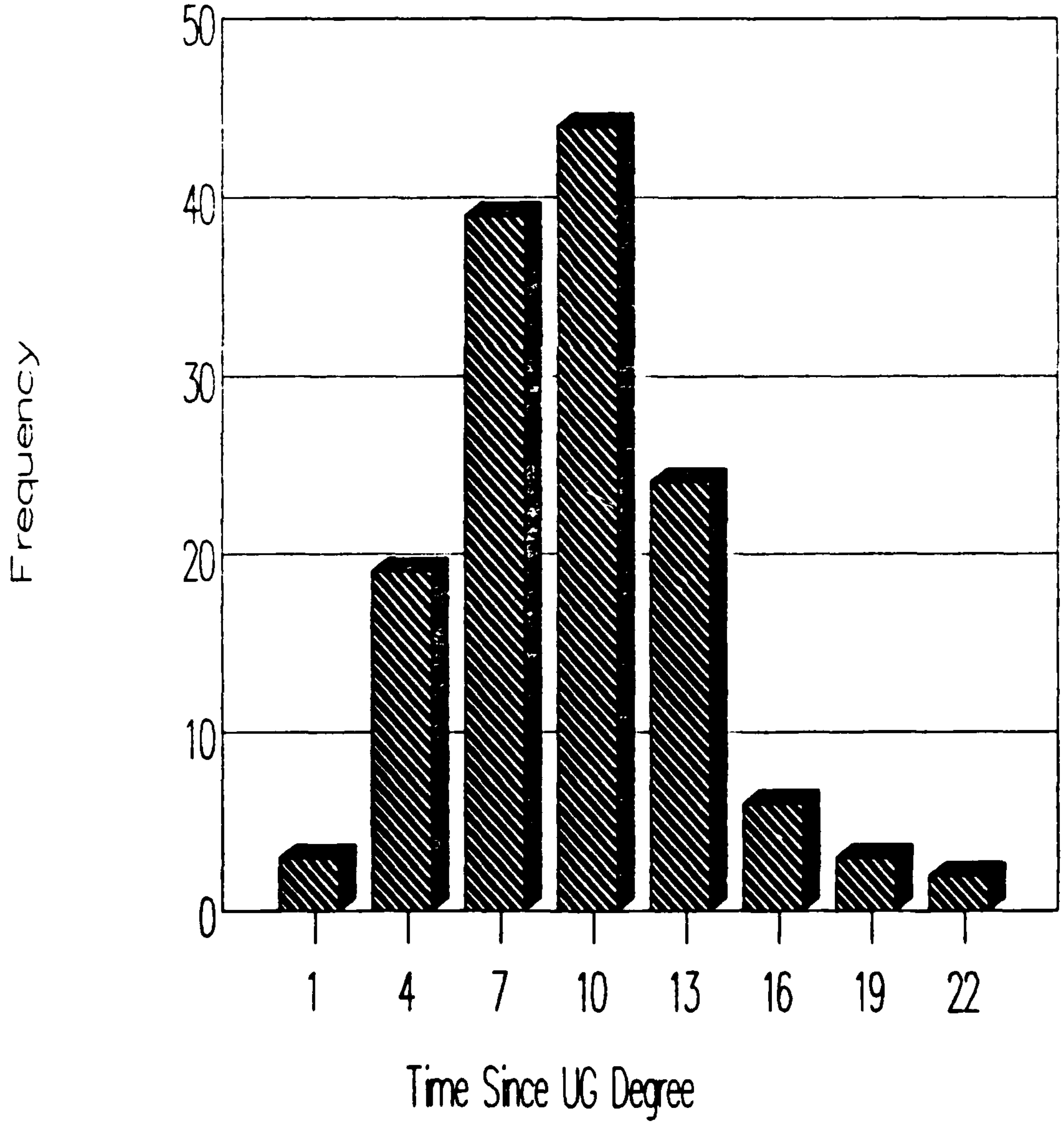
# Age Distribution

## GLM 86S-89S



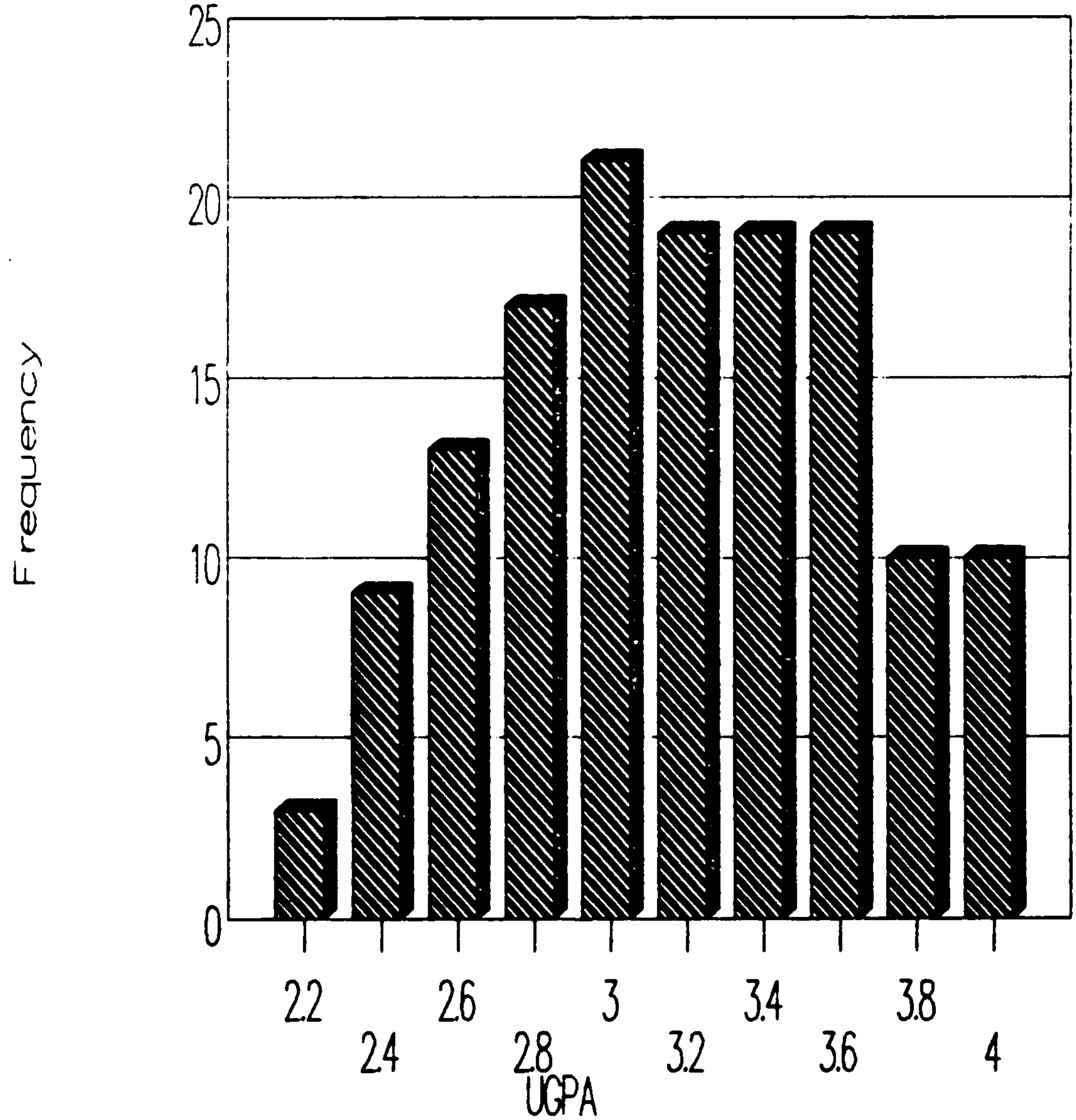
# Time Since UG Degree

# GLM 86S-89S



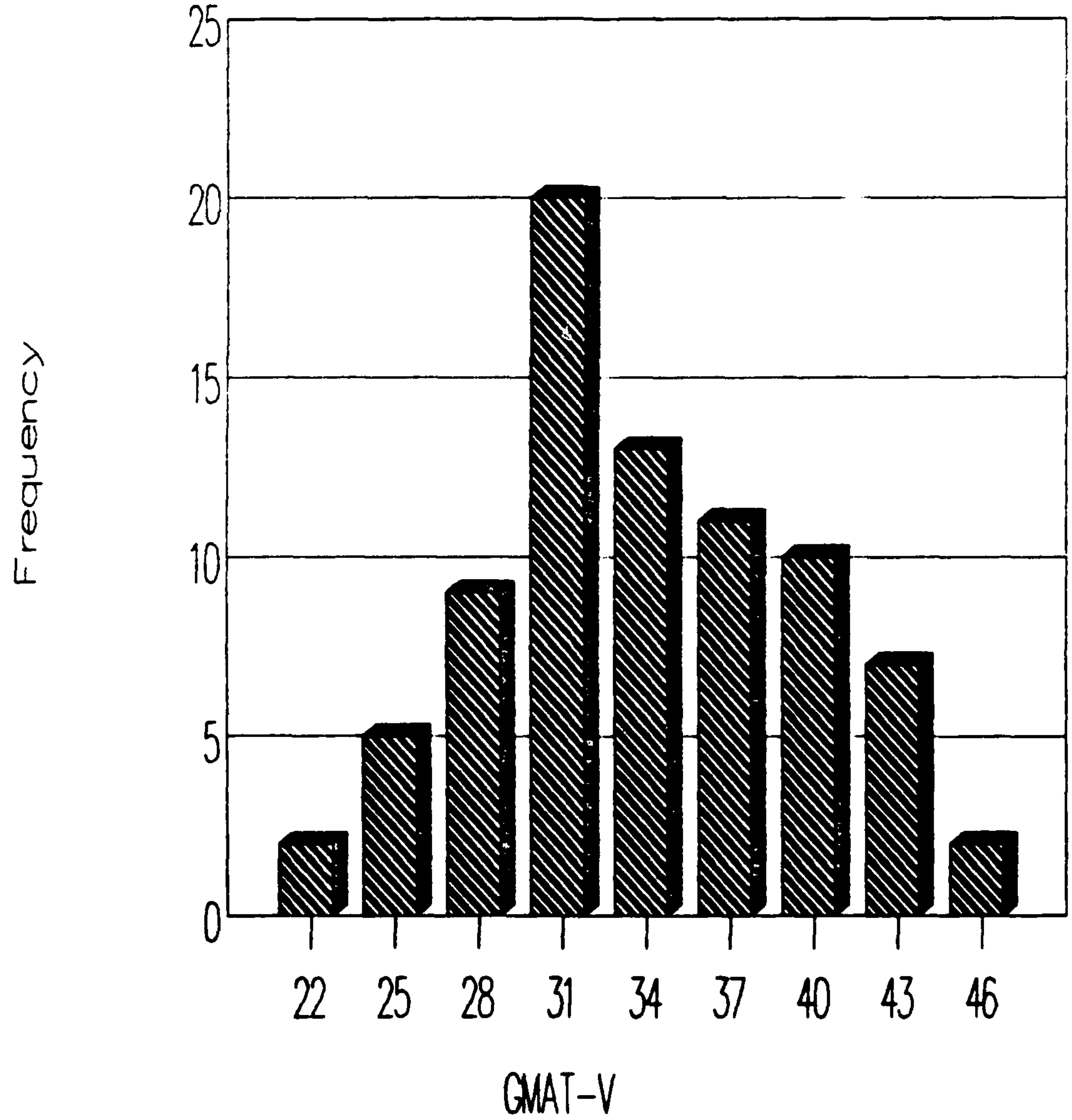
# UGPA Distribution

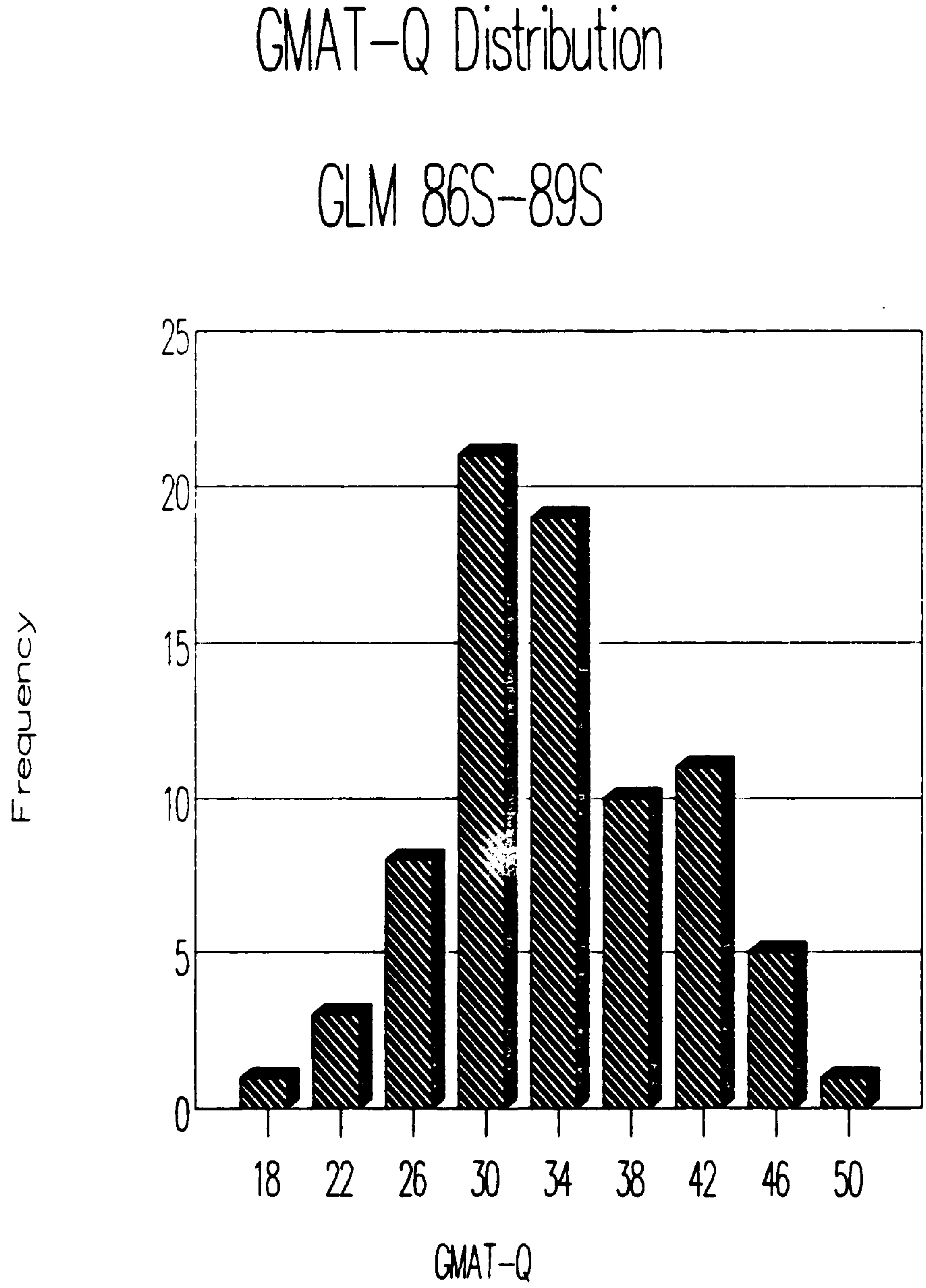
# GLM 86S-89S



# GMAT-V Distribution

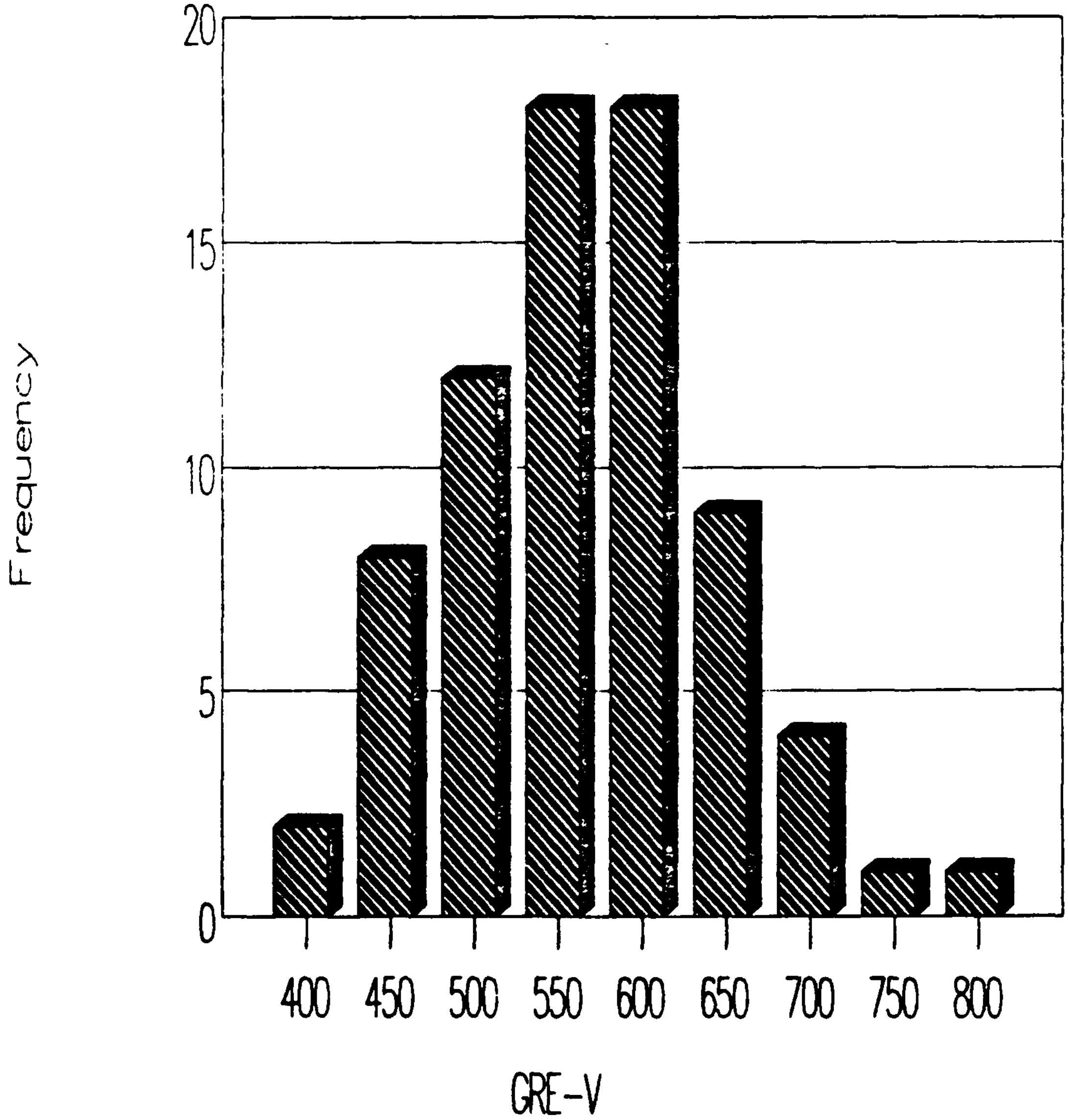
## GLM 86S-89S




GMAT-Q Distribution
GLM 86S-89S
Frequency
25
20
15
10
5
0
18
22
26
30
34
38
42
46
50
GMAT-Q

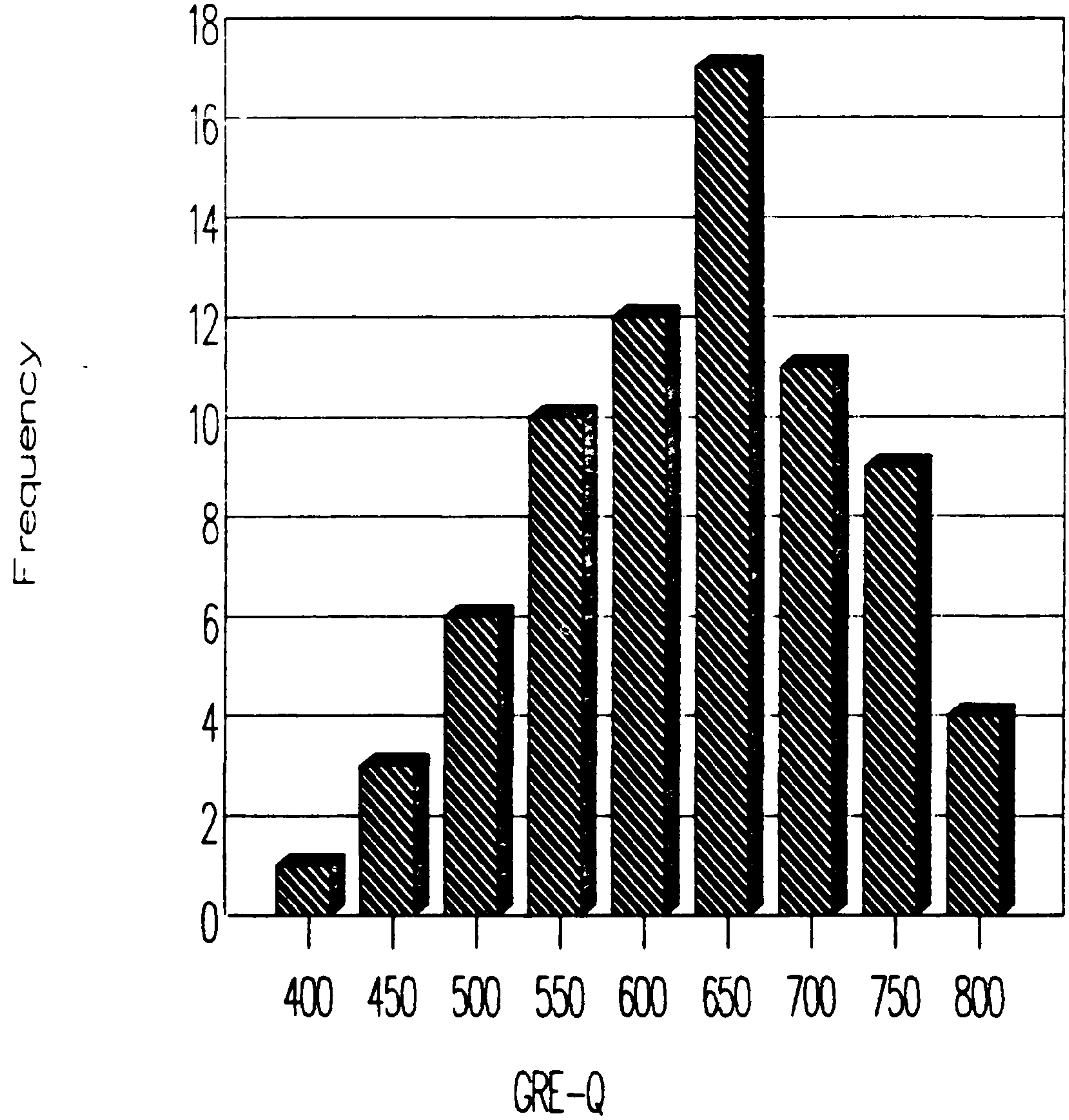
# GRE-V Distribution

## GLM 86S-89S



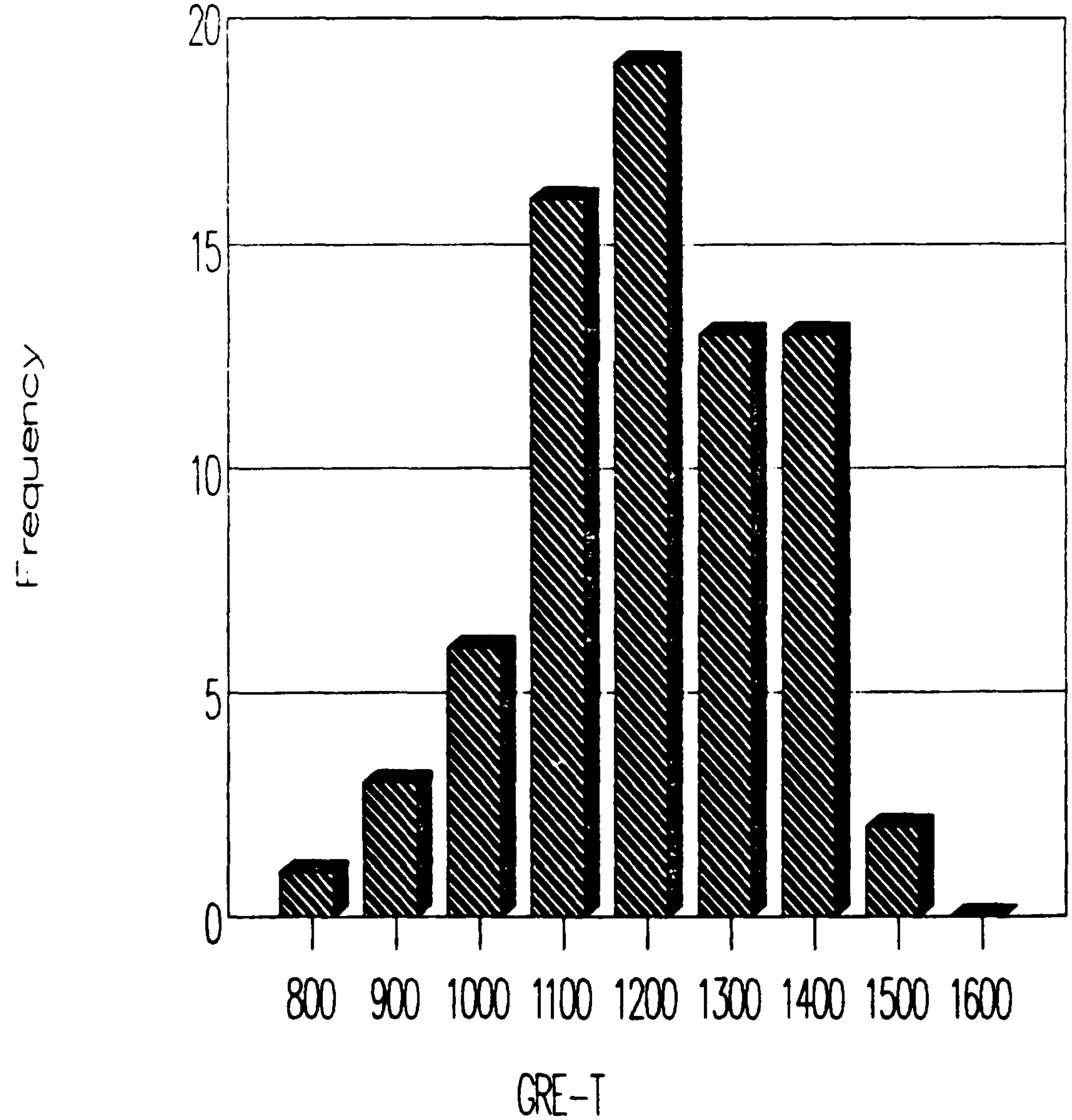
# GRE-Q Distribution

# GLM 86S-89S



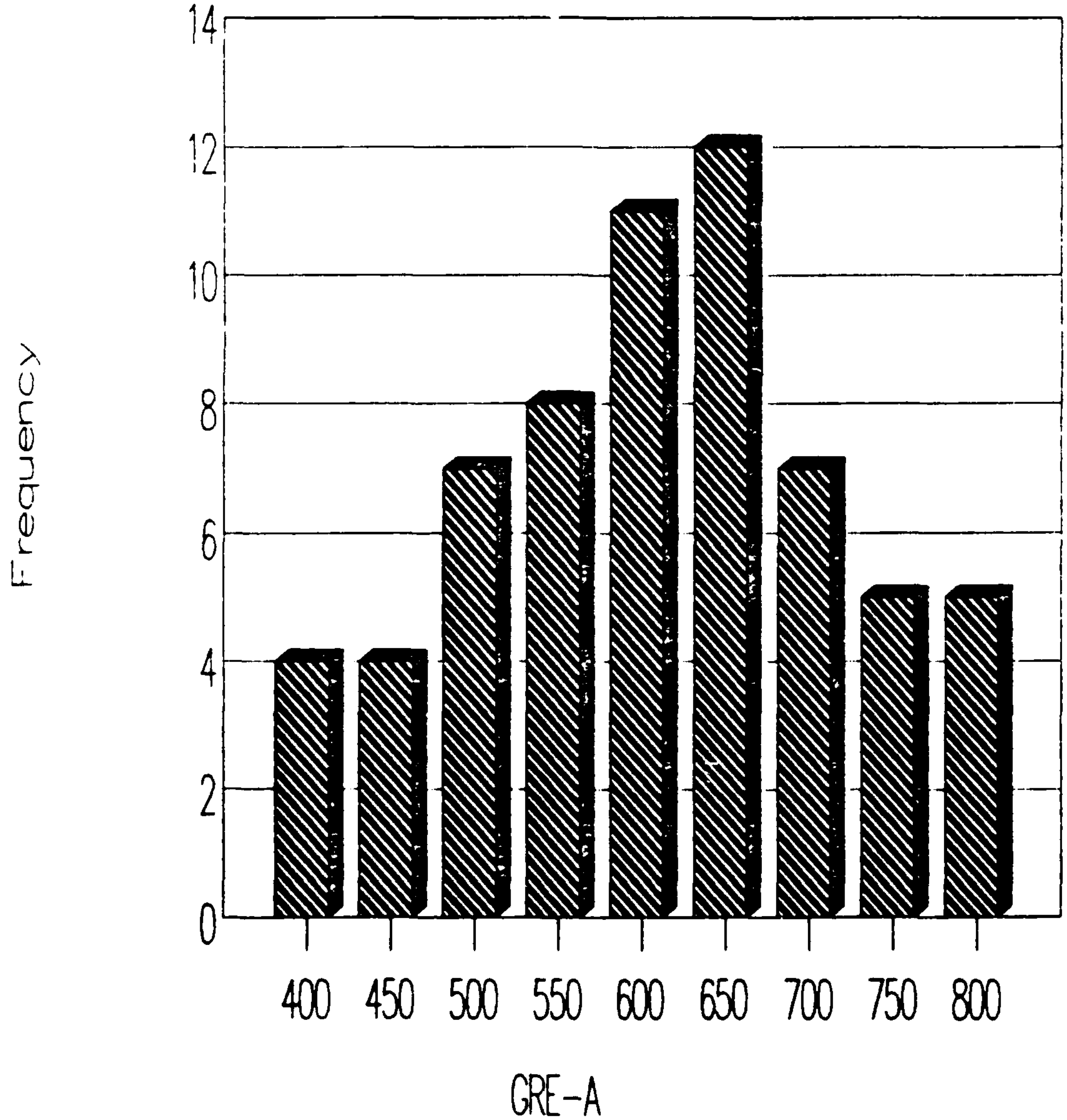
# GRE-T Distribution

## GLM 86S-89S



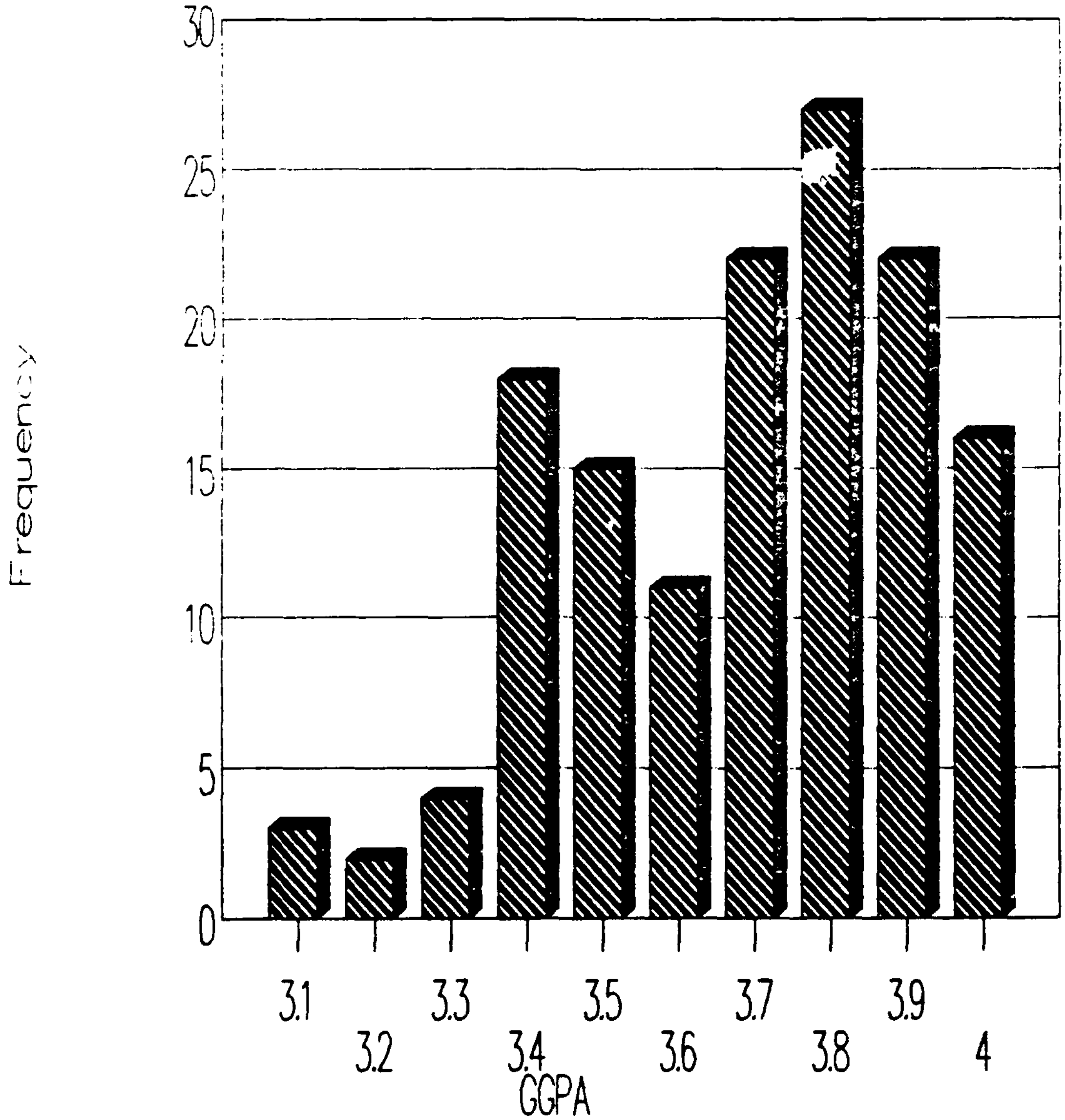
# GRE-A Distribution

# GLM 86S-89S



# GGPA Distribution

# GLM 86S-89S

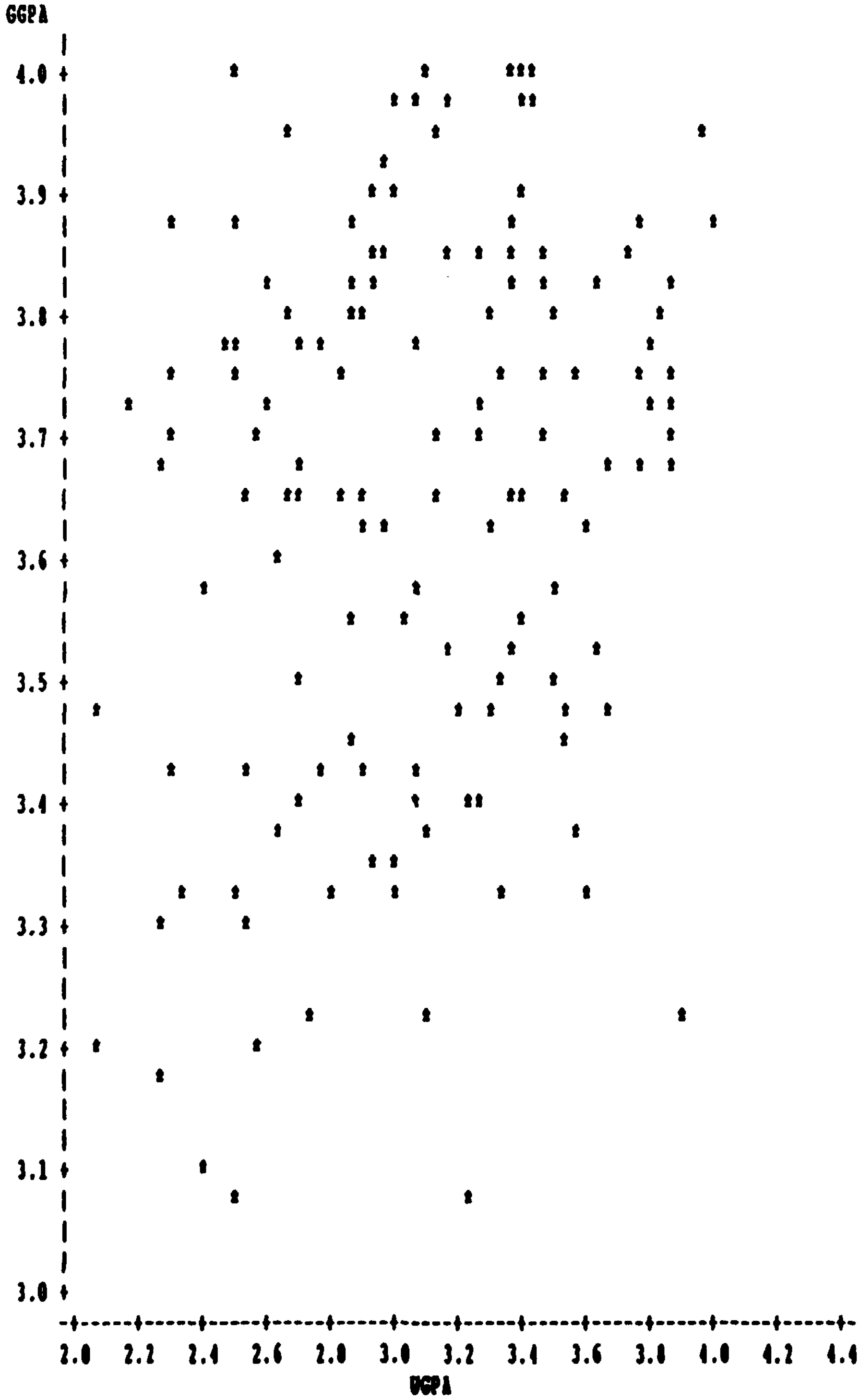


## Appendix H: Correlations, r, With GGPA

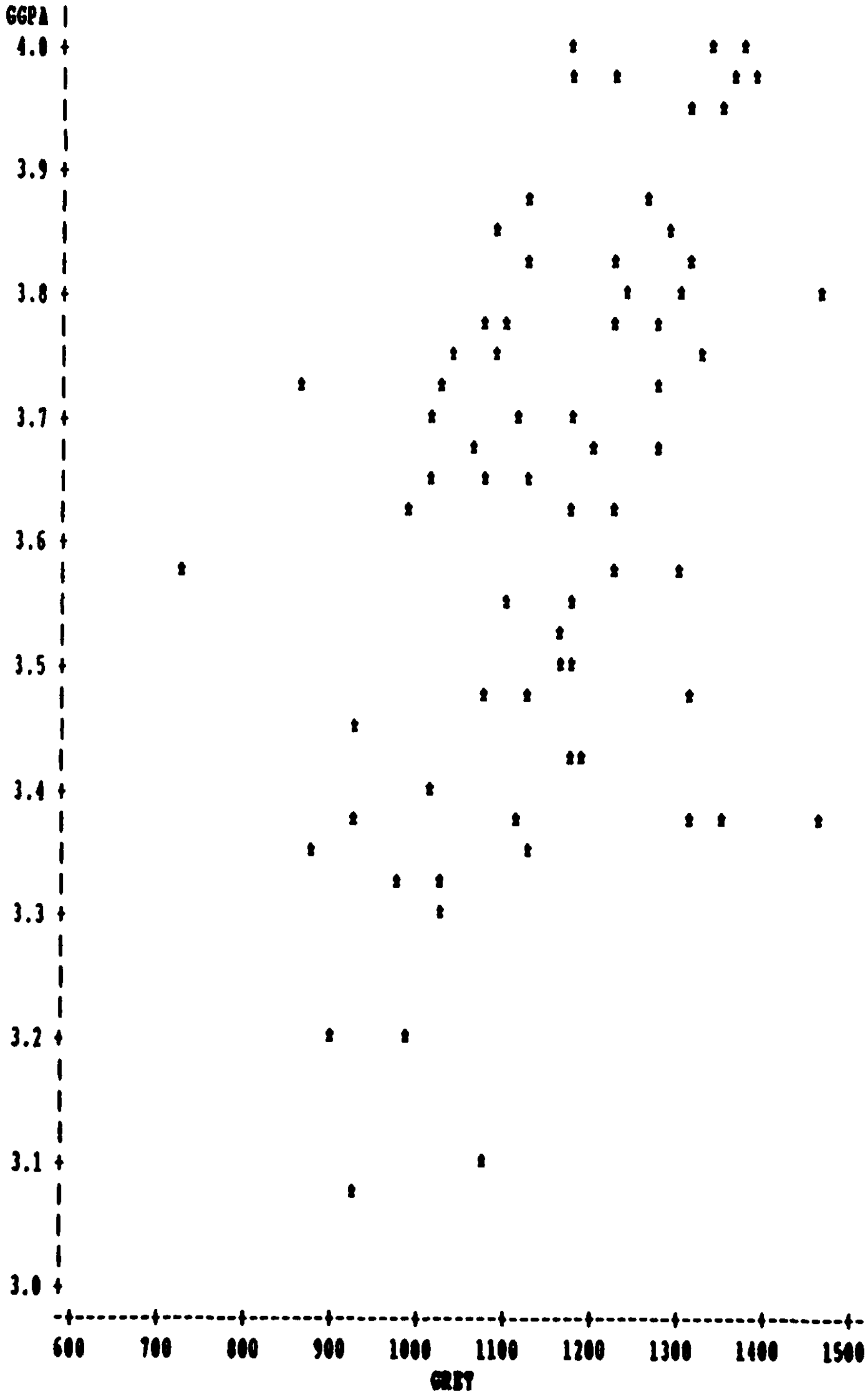
| Variable | N | p-value | r |
|---|---|---|---|
| COMM | 98 | .0263 | .2244 |
| AF | 140 | .7185 | .0307 |
| NAVY | 140 | .0574 | .1610 |
| CIV | 140 | .0822 | -.1474 |
| SEX | 140 | .8097 | -.0205 |
| RANK | 140 | .9058 | .0101 |
| AERO | 105 | .0430 | .1979 |
| ACAD | 114 | .0179 | .2214 |
| UDEG | 140 | .8161 | .0198 |
| MAJ | 140 | .3058 | .0872 |
| UGPA | 140 | .0037 | .2437 |
| GREV | 73 | .0045 | .3289 |
| GREQ | 73 | .0001 | .5021 |
| GRET | 73 | .0001 | .4827 |
| GREA | 63 | .0164 | .3013 |
| GMAV | 79 | .0001 | .4491 |
| GMAQ | 79 | .0032 | .3281 |
| GMAT | 79 | .0001 | .4544 |
| GDEG | 140 | .1267 | .1297 |
| GHRS | 139 | .0220 | .1941 |
| AGE | 138 | .2161 | .1060 |
| STIM | 99 | .5290 | .0640 |
| CTIM | 96 | .5096 | .0681 |
| DTIM | 140 | .9839 | .0017 |
| RATE | 139 | .0001 | .3707 |
| ACHS | 15 | .0500 | .5139 |
| ACHW | 15 | .0995 | .4414 |
| MATH | 140 | .1564 | .1204 |
| MATG | 135 | .0108 | .2188 |
| MA[illegible]T | 137 | .0932 | .1440 |
| RATGPA | 139 | .0001 | .4800 |

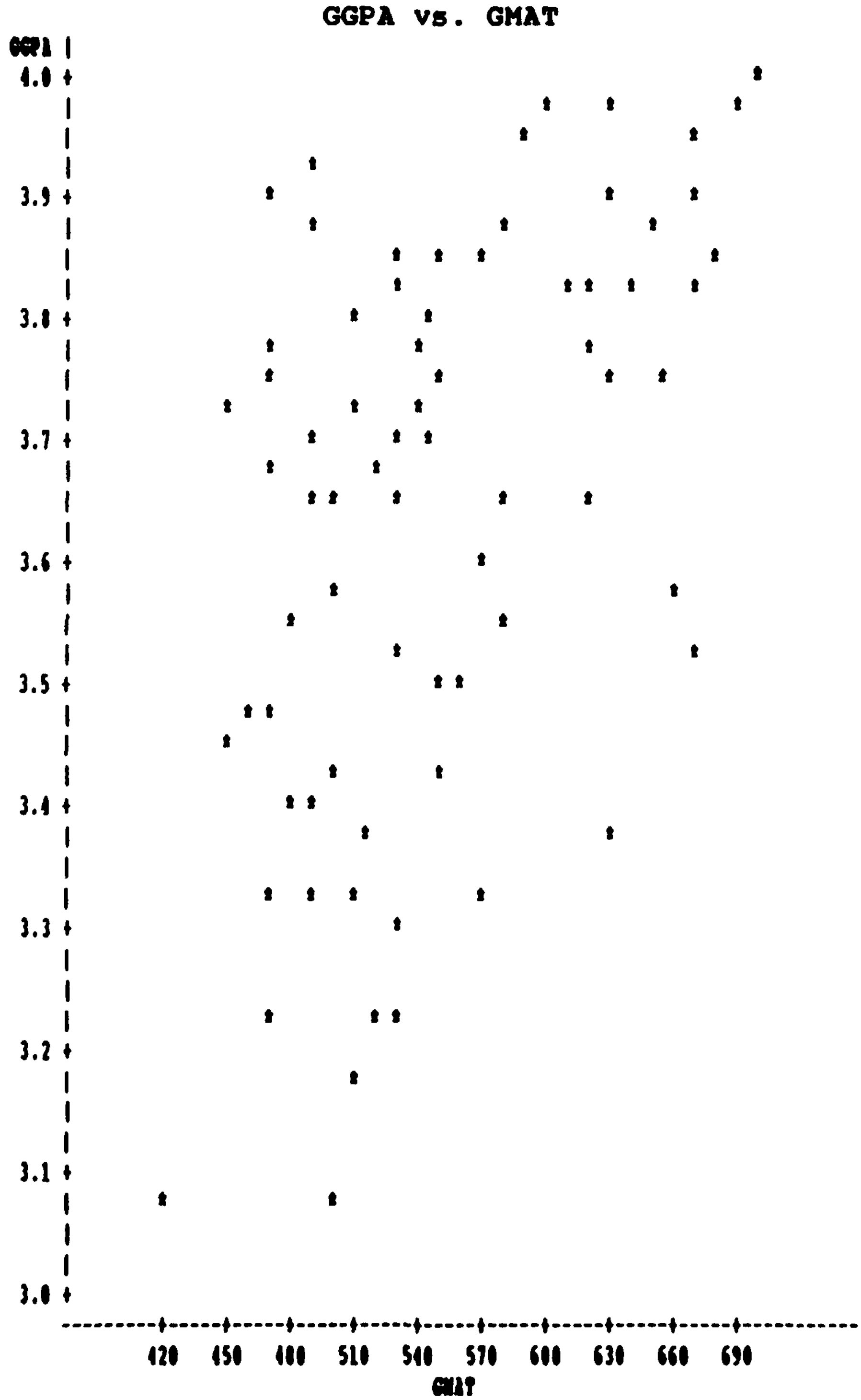
Appendix I: Scatterplots of Selected Predictors Versus GGPA

GGPA vs. UGPA



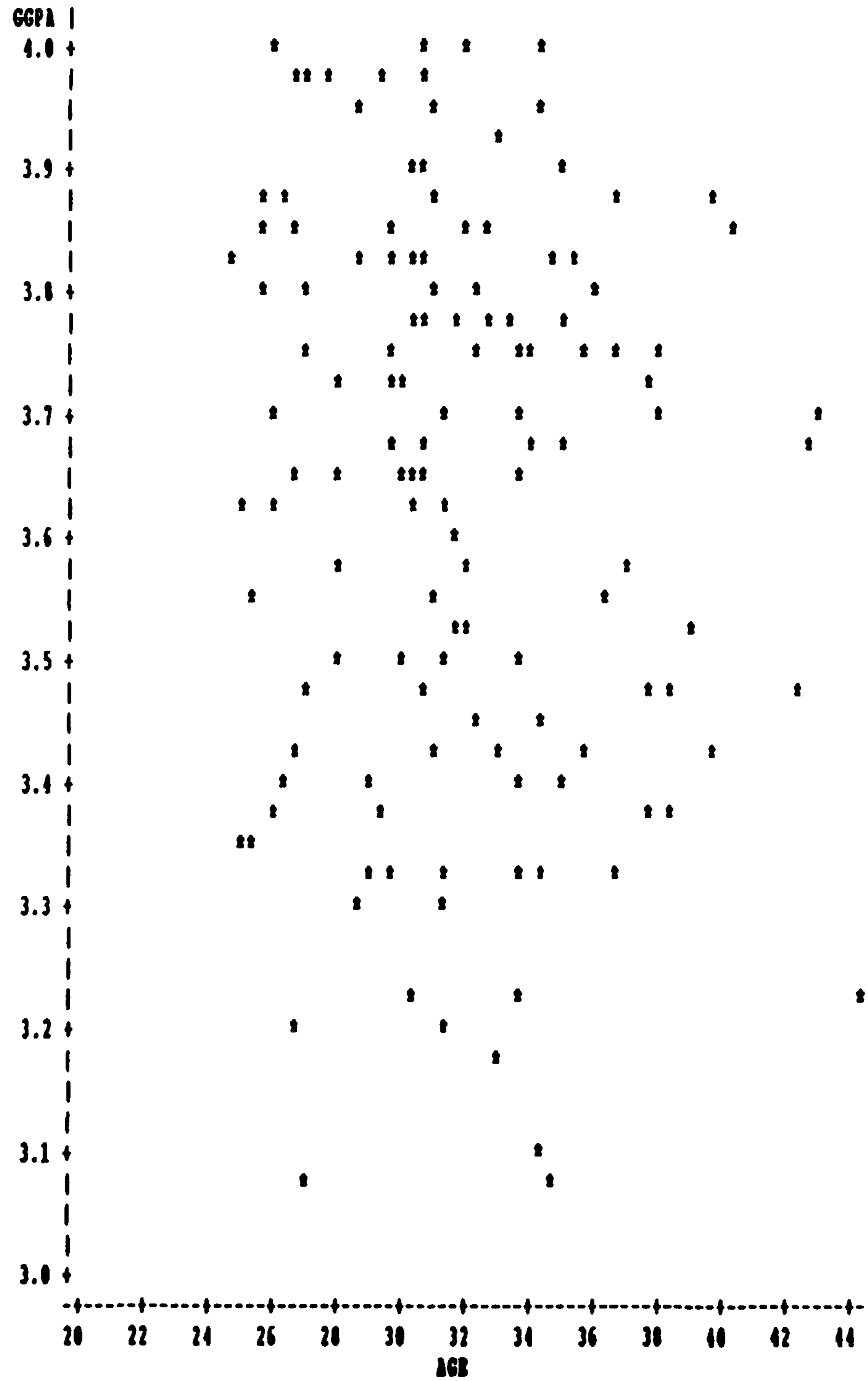
GGPA vs. GRET


GGPA
4.0
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3.0
600
700
800
900
1000
1100
1200
1300
1400
1500
GRET

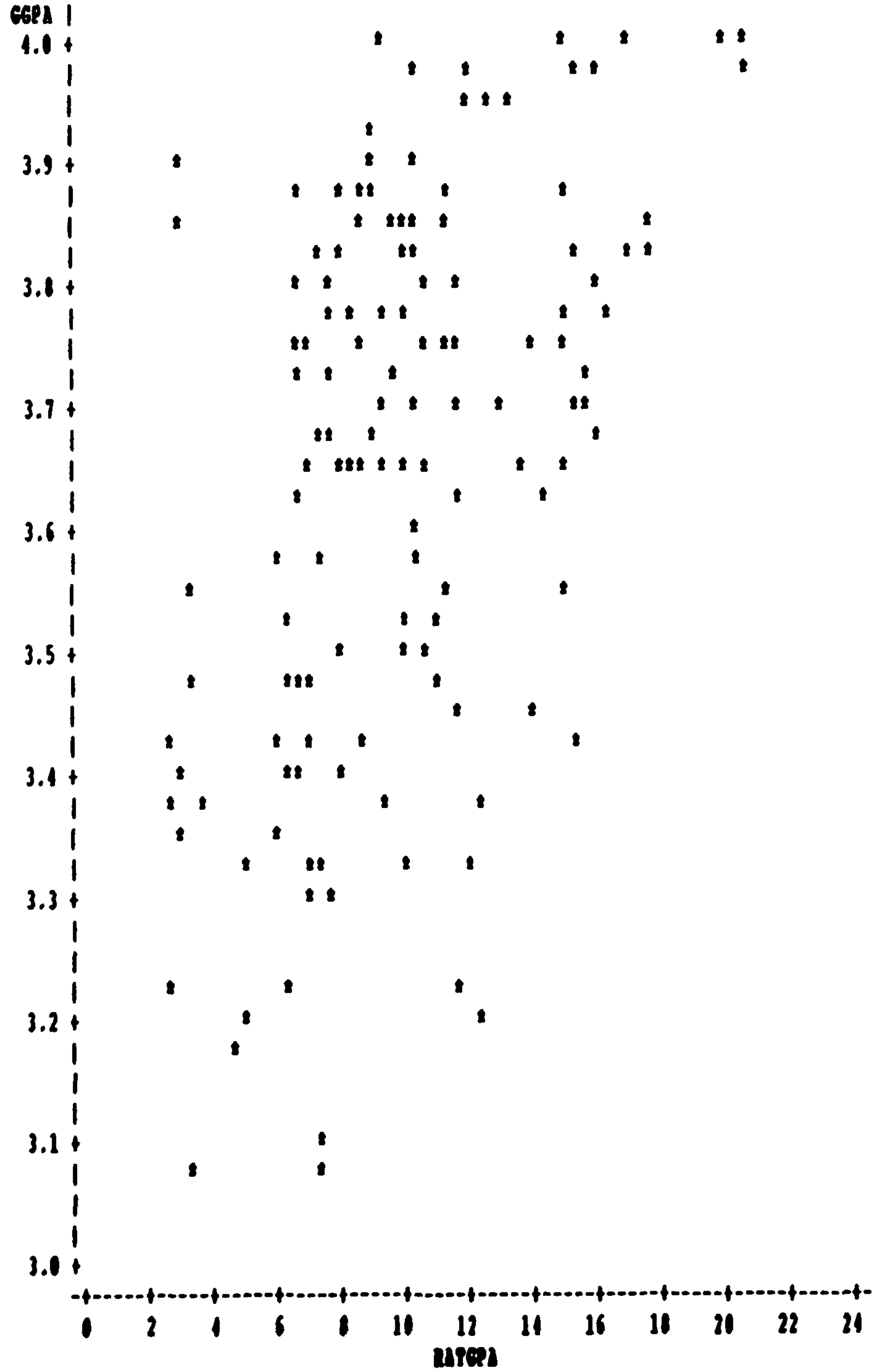


GGPA vs. GMAT
GGPA
4.0
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3.0
420 450 480 510 540 570 600 630 660 690
GMAT

GGPA vs. AGE


GGPA
4.0
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3.0
20
22
24
26
28
30
32
34
36
38
40
42
44
AGE

GGPA vs. RATGPA



Appendix J: Actual Versus Predicted GGPA For GRE Model

| Actual GGPA | Predicted GGPA | Studentized Residual | Lower95% Prediction Boundary | Upper95% Prediction Boundary |
|---|---|---|---|---|
| 3.6700 | 3.5671 | 0.7071 | 3.2561 | 3.8781 |
| 3.3430 | 3.3909 | -.337604 | 3.0733 | 3.7085 |
| 3.3250 | . | . | . | . |
| 3.9510 | 3.8454 | 0.7446 | 3.5275 | 4.1634 |
| 3.9850 | 3.8334 | 1.0281 | 3.5261 | 4.1406 |
| 3.6610 | 3.6006 | 0.4121 | 3.2915 | 3.9098 |
| 3.6430 | 3.5842 | 0.4020 | 3.2745 | 3.8939 |
| 3.9850 | 4.0124 | -.195855 | 3.6909 | 4.3339 |
| 3.0660 | 3.3478 | -1.989 | 3.0297 | 3.6659 |
| 3.6230 | 3.6172 | .0403691 | 3.3044 | 3.9299 |
| 3.6960 | 3.5758 | 0.8376 | 3.2610 | 3.8906 |
| 3.8030 | 3.7330 | 0.4773 | 3.4242 | 4.0418 |
| 3.7780 | 3.6956 | 0.5730 | 3.3814 | 4.0097 |
| 3.5600 | 3.6200 | -.409048 | 3.3110 | 3.9289 |
| 3.8870 | 3.7419 | 1.0035 | 3.4292 | 4.0546 |
| 3.5160 | 3.5512 | -.239375 | 3.2429 | 3.8594 |
| 3.1000 | 3.4204 | -2.2333 | 3.1056 | 3.7352 |
| 4.0000 | 3.9844 | 0.1106 | 3.6647 | 4.3042 |
| 3.9460 | 3.8401 | 0.7353 | 3.5263 | 4.1539 |
| 3.8260 | 3.9499 | -.862229 | 3.6355 | 4.2643 |
| 3.8180 | 3.8815 | -.439356 | 3.5688 | 4.1942 |
| 3.4980 | 3.6059 | -.738904 | 3.2959 | 3.9159 |
| 3.4260 | 3.5498 | -.863925 | 3.2345 | 3.8650 |
| 3.6330 | 3.8363 | -1.3924 | 3.5263 | 4.1464 |
| 3.6400 | 3.6679 | -.192943 | 3.3556 | 3.9803 |
| 3.8130 | 3.9296 | -.817287 | 3.6133 | 4.2459 |
| 3.7180 | 3.5842 | 0.9667 | 3.2604 | 3.9081 |
| 3.6550 | 3.6437 | .0781655 | 3.3308 | 3.9566 |
| 3.7080 | 3.8648 | -1.0991 | 3.5484 | 4.1811 |
| 3.3030 | 3.4947 | -1.3239 | 3.1823 | 3.8071 |
| 3.3750 | 3.4664 | -.682414 | 3.1353 | 3.7976 |
| 3.6760 | 3.7830 | -.742478 | 3.4693 | 4.0967 |
| 3.6250 | 3.5304 | 0.6545 | 3.2175 | 3.8433 |
| 3.5650 | 3.571( | -.046436 | 3.2541 | 3.8891 |
| 3.3910 | 3.4841 | -.637806 | 3.1739 | 3.7943 |
| 3.7260 | 3.4005 | 2.2591 | 3.0868 | 3.7143 |
| 3.7380 | 3.6798 | 0.3982 | 3.3700 | 3.9897 |
| 3.5780 | 3.5843 | -.043515 | 3.2699 | 3.8986 |
| 3.4730 | 3.5538 | -.550815 | 3.2452 | 3.8625 |
| 3.3680 | 3.6419 | -1.8724 | 3.3322 | 3.9515 |
| 3.8600 | 3.6449 | 1.4636 | 3.3366 | 3.9532 |
| 3.3710 | 3.3878 | -.119802 | 3.0673 | 3.7084 |
| 3.7390 | 3.5834 | 1.1019 | 3.2645 | 3.9024 |
| 3.7130 | 3.7544 | -.285544 | 3.4421 | 4.0666 |
| 3.7050 | 3.7511 | -.318833 | 3.4382 | 4.0640 |

| Actual GGPA | Predicted GGPA | Studentized Residual | Lower95% Prediction Boundary | Upper95% Prediction Boundary |
|---|---|---|---|---|
| 4.0000 | 3.6344 | 2.4613 | 3.3292 | 3.9396 |
| 3.2010 | 3.4822 | -2.0178 | 3.1600 | 3.8044 |
| 3.9850 | 3.9463 | 0.2703 | 3.6308 | 4.2619 |
| 3.7710 | 3.7421 | 0.2019 | 3.4269 | 4.0572 |
| 4.0000 | 3.8318 | 1.1678 | 3.5180 | 4.1456 |
| 3.6780 | 3.5792 | 0.6892 | 3.2641 | 3.8944 |
| 3.5450 | 3.4637 | 0.5668 | 3.1488 | 3.7786 |
| 3.7950 | 3.8786 | -.579463 | 3.5653 | 4.1919 |
| 3.7800 | 3.4782 | 2.0706 | 3.1676 | 3.7888 |
| 3.5100 | 3.6631 | -1.0344 | 3.3568 | 3.9694 |
| 4.0000 | 4.0015 | -.010799 | 3.6805 | 4.3225 |
| 3.4600 | 3.5374 | -.533689 | 3.2256 | 3.8493 |
| 3.8450 | 3.8597 | -0.10236 | 3.5454 | 4.1741 |
| 3.5730 | 3.4115 | 1.2402 | 3.0743 | 3.7486 |

## Appendix K: Actual Versus Predicted GGPA For GMAT Model

| Actual GGPA | Predicted GGPA | Studentized Residual | Lower95% Prediction Boundary | Upper95% Prediction Boundary |
|---|---|---|---|---|
| 3.3080 | 3.4122 | -.640201 | 3.0693 | 3.7552 |
| 3.7750 | 3.8372 | -.389993 | 3.4883 | 4.1862 |
| 3.2200 | 3.4942 | -1.6671 | 3.1546 | 3.8339 |
| 3.9850 | 3.8508 | 0.8825 | 3.4886 | 4.2130 |
| 3.7000 | 3.6836 | 0.0993 | 3.3459 | 4.0213 |
| 3.9850 | 4.1666 | -1.2109 | 3.8010 | 4.5322 |
| 3.0660 | 3.4494 | -2.3446 | 3.1078 | 3.7910 |
| 3.3180 | 3.5519 | -1.424 | 3.2117 | 3.8921 |
| 3.8030 | 3.6596 | 0.8669 | 3.3216 | 3.9976 |
| 3.8220 | 3.6985 | 0.7461 | 3.3608 | 4.0363 |
| 3.6650 | 3.6389 | 0.1580 | 3.3002 | 3.9776 |
| 3.8240 | 3.6019 | 1.3426 | 3.2640 | 3.9397 |
| 3.8840 | 3.7735 | 0.6792 | 3.4304 | 4.1165 |
| 3.7700 | 3.7320 | 0.2496 | 3.3700 | 4.0940 |
| 3.4650 | 3.4893 | -.147949 | 3.1496 | 3.8290 |
| 3.3200 | 3.5721 | -1.5544 | 3.2281 | 3.9162 |
| 3.9460 | 3.9145 | 0.1943 | 3.5704 | 4.2586 |
| 3.8540 | 3.7228 | 0.7940 | 3.3845 | 4.0612 |
| 3.2330 | 3.3947 | -1.002 | 3.0490 | 3.7404 |
| 3.6610 | 3.5129 | 0.8984 | 3.1739 | 3.8520 |
| 3.8260 | 3.9574 | -.829957 | 3.6062 | 4.3086 |
| 3.4180 | 3.4684 | -.306784 | 3.1280 | 3.8087 |
| 3.7520 | 3.8382 | -.567197 | 3.4759 | 4.2005 |
| 3.8470 | 3.5742 | 1.6506 | 3.2360 | 3.9123 |
| 3.9030 | 3.8699 | 0.2044 | 3.5254 | 4.2144 |
| 3.4210 | 3.4680 | -.290871 | 3.1224 | 3.8135 |
| 3.8000 | 3.5992 | 1.2180 | 3.2602 | 3.9383 |
| 3.7060 | 3.6675 | 0.2359 | 3.3250 | 4.0100 |
| 3.8130 | 3.9101 | -.601664 | 3.5645 | 4.2557 |
| 3.7180 | 3.5796 | 0.9009 | 3.2201 | 3.9390 |
| 3.8210 | 3.7044 | 0.7048 | 3.3665 | 4.0423 |
| 3.7130 | 3.5761 | 0.8275 | 3.2382 | 3.9141 |
| 3.6380 | 3.7450 | -.701891 | 3.3836 | 4.1065 |
| 3.9100 | 3.8639 | 0.2874 | 3.5166 | 4.2112 |
| 3.6600 | 3.6627 | -.016191 | 3.3246 | 4.0008 |
| 3.4280 | 3.7160 | -1.7468 | 3.3769 | 4.0550 |
| 3.8520 | 3.6971 | 1.0253 | 3.3333 | 4.0609 |
| 3.5650 | 3.7093 | -.890305 | 3.3650 | 4.0536 |
| 3.7380 | 3.7205 | 0.1078 | 3.3771 | 4.0639 |
| 3.7260 | 3.5016 | 1.3627 | 3.1622 | 3.8410 |
| 3.1680 | 3.4346 | -1.6334 | 3.0924 | 3.7768 |
| 3.5510 | 3.6160 | -.413503 | 3.2626 | 3.9694 |
| 3.8600 | 3.6442 | 1.3648 | 3.2926 | 3.9958 |
| 3.0850 | 3.4300 | -2.1283 | 3.0857 | 3.7743 |

| Actual GGPA | Predicted GGPA | Studentized Residual | Lower95% Prediction Boundary | Upper95% Prediction Boundary |
|---|---|---|---|---|
| 3.4080 | 3.4505 | -.262198 | 3.1059 | 3.7951 |
| 3.8600 | 3.7945 | 0.3993 | 3.4541 | 4.1348 |
| 3.3710 | 3.4128 | -.257614 | 3.0689 | 3.7567 |
| 3.7390 | 3.7016 | 0.2288 | 3.3599 | 4.0434 |
| 3.9500 | 3.8243 | 0.7661 | 3.4837 | 4.1649 |
| 3.3950 | 3.3917 | .0206386 | 3.0453 | 3.7381 |
| 3.8700 | 3.6899 | 1.0906 | 3.3515 | 4.0282 |
| 3.9850 | 3.9806 | .0274031 | 3.6326 | 4.3287 |
| 4.0000 | 4.0682 | -.434675 | 3.7144 | 4.4220 |
| 3.4980 | 3.5605 | -.378432 | 3.2224 | 3.8987 |
| 3.5450 | 3.6789 | -.896853 | 3.3120 | 4.0457 |
| 3.6030 | 3.7072 | -.630131 | 3.3693 | 4.0451 |
| 3.7800 | 3.4206 | 2.2200 | 3.0759 | 3.7653 |
| 3.4630 | 3.3750 | 0.5432 | 3.0304 | 3.7196 |
| 3.8000 | 3.4779 | 1.9626 | 3.1375 | 3.8183 |
| 3.7530 | 3.6279 | 0.7605 | 3.2882 | 3.9676 |
| 3.4580 | 3.6902 | -1.4346 | 3.3455 | 4.0349 |
| 3.5730 | 3.6111 | -.230989 | 3.2722 | 3.9500 |

## Appendix L: Validation Data From Class 89S For GRE Model

| Actual GGPA | Predicted GGPA | (Actual - Predicted) | (Actual - Predicted)$^2$ |
|---|---|---|---|
| 3.380 | 3.866 | -0.4858 | 0.2360 |
| 3.800 | 3.829 | -0.0290 | 0.0008 |
| 3.375 | 3.706 | -0.3314 | 0.1099 |
| 3.463 | 3.554 | -0.0907 | 0.0082 |
| 3.886 | 3.589 | 0.2966 | 0.0879 |
| 3.786 | 3.620 | 0.1662 | 0.0276 |
| 3.431 | 3.741 | -0.3099 | 0.0960 |
| 3.965 | 3.733 | 0.2321 | 0.0539 |
| 3.816 | 3.643 | 0.1728 | 0.0299 |
| 3.463 | 3.669 | -0.2058 | 0.0424 |
| 3.759 | 3.683 | 0.0759 | 0.0058 |
| 3.319 | 3.389 | -0.0701 | 0.0049 |
| 3.194 | 3.327 | -0.1330 | 0.0177 |
| 3.355 | 3.367 | -0.0116 | 0.0001 |
| | | | ------- |
| | | SSE = | 0.7211 |

$$RMSE = (SSE / N)^{1/2}$$

$$= (.7211 / 14)^{1/2}$$

$$= 0.2269$$

Appendix M: Validation Data From Class 89S For GMAT Model

| Actual GGPA | Predicted GGPA | (Actual - Predicted) | (Actual - Predicted)$^2$ |
|---|---|---|---|
| 3.520 | 3.908 | -0.3876 | 0.1502 |
| 3.865 | 3.750 | 0.1151 | 0.0132 |
| 3.375 | 3.802 | -0.4273 | 0.1826 |
| 3.650 | 3.967 | -0.3171 | 0.1005 |
| 3.322 | 3.637 | -0.3145 | 0.0989 |
| 3.501 | 3.636 | -0.1346 | 0.0181 |
| 3.537 | 3.626 | -0.0890 | 0.0079 |
| 3.221 | 3.541 | -0.3196 | 0.1021 |
| 3.642 | 3.372 | 0.2700 | 0.0729 |
| 3.886 | 3.366 | 0.5200 | 0.2704 |
| 3.918 | 3.726 | 0.1918 | 0.0368 |
| 3.698 | 3.633 | 0.0651 | 0.0042 |
| 3.319 | 3.464 | -0.1446 | 0.0209 |
| 3.749 | 3.542 | 0.2074 | 0.0430 |
| 3.664 | 3.576 | 0.0881 | 0.0078 |
| 3.900 | 3.472 | 0.4275 | 0.1828 |
| 3.722 | 3.477 | 0.2454 | 0.0602 |
| | | | ------- |
| | | | SSE = 1.3727 |

$$\text{RMSE} = (\text{SSE} / N)^{1/2}$$

$$= (1.3727 / 17)^{1/2}$$

$$= 0.2842$$

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## Vita

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| 6a. NAME OF PERFORMING ORGANIZATION<br>School of Systems and Logistics<br>6b. OFFICE SYMBOL (If applicable)<br>AFIT/LSY | 7a. NAME OF MONITORING ORGANIZATION |
| 6c. ADDRESS (City, State, and ZIP Code)<br>Air Force Institute of Technology<br>Wright-Patterson AFB OH 45433-6583 | 7b. ADDRESS (City, State, and ZIP Code) |
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| 8c. ADDRESS (City, State, and ZIP Code) | 10. SOURCE OF FUNDING NUMBERS<br>PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO. / WORK UNIT ACCESSION NO. |

11. TITLE (Include Security Classification)
A REGRESSION MODEL FOR PREDICTING ACADEMIC SUCCESS OF PROSPECTIVE STUDENTS IN THE AFIT GRADUATE LOGISTICS MANAGEMENT PROGRAM

12. PERSONAL AUTHOR(S)
Spangler, Mark E., B.S., Captain, USAF

| 13a. TYPE OF REPORT | 13b. TIME COVERED | 14. DATE OF REPORT (Year, Month, Day) | 15. PAGE COUNT |
|---|---|---|---|
| MS Thesis | FROM ____ TO ____ | 1989 December | 102 |

16. SUPPLEMENTARY NOTATION

| 17. COSATI CODES | | | 18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number) |
|---|---|---|---|
| FIELD | GROUP | SUB-GROUP | Mathematical Prediction, Regression Analysis, Correlation Techniques, Personnel Selection, Education. (EG) |
| 05 | 09 | | |
| | | | |


19. ABSTRACT (Continue on reverse if necessary and identify by block number)

Thesis Advisor: Kenneth W. Bauer, Jr., Major
Assistant Professor of Operations Research
Department of Operational Sciences

Approved for public release: IAW AFR 190-1.

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| 20. DISTRIBUTION/AVAILABILITY OF ABSTRACT | 21. ABSTRACT SECURITY CLASSIFICATION |
|---|---|
| ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS | UNCLASSIFIED |

| 22a. NAME OF RESPONSIBLE INDIVIDUAL | 22b. TELEPHONE (Include Area Code) | 22c. OFFICE SYMBOL |
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DD Form 1473, JUN 86 Previous editions are obsolete.

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Counselors in the Admissions Division at the Air Force Institute of Technology currently determine academic eligibility of graduate program candidates subjectively on the basis of criteria defining minimum acceptable undergraduate grade-point averages (UGPA) and graduate admissions test scores. The determination could be made more uniformly and efficiently by a regression model that could predict each candidate's final graduate grade-point average (GGPA) given his or her UGPA, test scores, and other background information. This study developed and validated such a model using data collected on 140 students of the Graduate Logistics Management (GLM) classes of 1986 through 1989.

The predictor variable found to be most highly correlated with GGPA was need for achievement. Stepwise regression was used to select from among 31 predictors, including admissions test scores, UGPA, age, rank, math GPA, and time since undergraduate degree. Two models were thus developed--one for students with GRE scores and one for students with GMAT scores.

The models gave $R^2$ values of .59 and .54. This relative success was attributed to three factors: 1) considerable variety of input factors among GLM students; 2) the selection of a single, uniform curriculum for study; and 3) a highly correlated predictor formed as the product of UGPA and a rating of the admissions competitiveness of the undergraduate institution. This predictor acted as the UGPA adjusted for the difficulty in achieving that average.

Regression assumptions were checked through residual analysis. A graphical demographic report is included.